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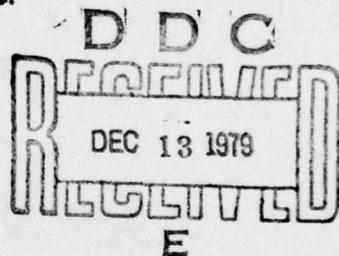
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INTELLIGIBILITY THRESHOLD LEVEL (ITL) RATINGS OF SOME CURRENT DIGITAL VOICE COMMUNICATIONS PROCESSORS

Caldwell P. Smith



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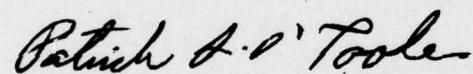
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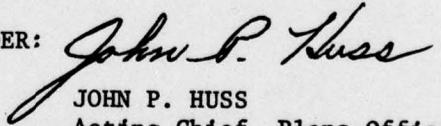
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A negative binomial probability distribution was found to give good agreement with empirical data distributions of speech intelligibility scores.

A new performance rating for voice communications devices, termed an intelligibility threshold level (ITL), was conceived as a means of taking these findings into consideration in establishing a measure of intelligibility performance that is an estimate of an intelligibility value that the majority (rather than the simple average) of intelligibility scores for a voice processor will equal or exceed, at a specified confidence level established in relation to the sample size used in obtaining the rating.

It is proposed that an ITL rating is a more meaningful assessment of the degree of risk involved in misunderstanding voice messages or causing time to be lost in requiring messages to be repeated.

It was shown that ITL's can be determined by two alternative methods: by rank-ordering the intelligibility scores for a processor and constructing the cumulative distribution of data and its confidence band, or by using a negative binomial probability model for the data distribution.

Chi-squared tests indicated that in most cases the negative binomial probability model gave a reasonable approximation to the data distribution.

Intelligibility threshold levels (ITL's) estimated with the negative binomial probability model differed by at most one quantum value (3.125) from the ITL values determined from the empirical distributions.

It is recommended that future speech intelligibility tests and evaluations of digital voice communications processors and systems include an analysis of the data to determine the 80 percent ITL's at 95 percent probability, that is, determine the intelligibility level for which there is a 95 percent probability that 80 percent of the population of intelligibility scores (for individual speakers and phonetic features) will equal or exceed.

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Intelligibility Threshold Level (ITL) Ratings of Some Current Digital Voice Communications Processors

I. INTRODUCTION

Over the past several years there has been an opportunity to study speech intelligibility data obtained from tests and evaluations of a wide variety of processors for digital speech communications applications. These studies have led to a conclusion that average intelligibility scores currently used to specify intelligibility performance fall short of providing adequate ratings of intelligibility, and that a need exists for an alternative rating for speech intelligibility that takes into consideration dispersion and highly skewed distributions of scores that characterize data obtained with multiple speakers and diagnostic intelligibility testing. This report presents some of those findings and presents a new concept for a speech intelligibility rating to supplement or replace average scores that rate the intelligibility performance of speech communications systems and devices.

1.1 Diagnostic Rhyme Test (DRT)

The intelligibility performance of speech communications processors is for the most part evaluated with the Diagnostic Rhyme Test or DRT. This is a test that grew out of research on very-low-data-rate digital speech communications by the method of voice pattern-matching. A speech intelligibility test method was needed to provide diagnostic intelligibility data, that is to assess separately the

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intelligibility obtained for each of the categories of phonetic events, as well as assessing overall or "total" intelligibility. This need was critical for evaluating performance and guiding the research in connection with the voice pattern-coding technique, as it was considered essential that the library of spectral patterns of speech should fully accommodate the range of allophones of conversational speech. A diagnostic intelligibility test method was required in order to assess whether this objective had been met and to identify any deficiencies in analysis and synthesis of the various speech sounds. The Diagnostic Rhyme Test or DRT was developed to fulfill this need. It quickly became apparent that the DRT combined unique properties of resolving power and sensitivity for assessing speech intelligibility performance, as well as being extremely efficient and economical for obtaining detailed intelligibility analyses with minimum investments in processing time and listener crew time. An initial single-speaker version of the DRT which was used in a first survey of the intelligibility performance of vocoder technology in 1967 was subsequently expanded to a multiple-speaker version that was used in a second survey of intelligibility performance of vocoder technology in 1972. Since that time additional multiple-speaker versions of the DRT including men and women speakers have been recorded with close-talking dynamic, carbon, and pressure-gradient (noise-cancelling) microphones; recording conditions have included quiet environments and talkers in various simulations of acoustic noise environments of interest in the Department of Defense (DOD). These intelligibility test recordings have been widely used in the DOD for evaluating intelligibility of a variety of digital and analog speech processing techniques and hardware. Intelligibility data obtained in these tests has provided the opportunity to closely examine such questions as intelligibility differences found among different speakers and variations in intelligibility of the various phonetic features.

1.2 Speaker Variability

A general finding has been that intelligibility scores are typically characterized by significant differences among speakers. Examples of this effect are presented in Figures 1 and 2 which present rankings of nine speakers (six male and three female) obtained from tests of three categories of voice processors, consisting of approximately a dozen each of narrowband, mediumband, and wideband devices. The speaker scores presented are the averages for all processors of each group. The Newman-Keuls test of significant differences among means was utilized in determining significant differences among the mean scores, leading to the rankings shown by the brackets. Data from the tests with the high-quality dynamic microphone indicated that the speakers fell into four categories which overlapped except in the case of the narrowband processors. Data obtained with

Nine - Speaker Diagnostic Rhyme Test

<u>2400 BPS Systems</u>	<u>3600 & 4800 BPS Systems</u>	<u>Wideband Systems</u>
87.7 CH]	88.0 CH]	89.2 RH]
85.2 RH]	86.1 RH]	88.8 CH]
83.5 LL]	86.0 LL]	88.5 LL]
81.0 PK]	83.4 PK]	86.3 PK]
79.7 MP(Fem.)]	82.1 BV]	85.2 LS(Fem.)]
79.7 BV]	80.5 LS(Fem.)]	84.0 MP(Fem.)]
79.5 JE]	79.8 MP(Fem.)]	83.5 JE]
78.6 LS(Fem.)]	79.4 JE]	83.3 JS(Fem.)]
75.7 JS(Fem.)]	78.4 JS(Fem.)]	82.3 BV]

The Newman - Keuls test of differences between means indicated that Scores within brackets did not differ significantly.

Figure 1. Mean Speaker Scores Obtained with a Dynamic Microphone

Nine - Speaker Diagnostic Rhyme Test

<u>2400 BPS Systems</u>	<u>3600 & 4800 BPS Systems</u>	<u>Wideband Systems</u>
83.1 CH]	85.0 CH]	91.4 CH]
82.5 RH]	83.8 RH]	89.9 LL]
79.8 LL]	81.4 LL]	89.0 RH]
77.9 PK]	80.2 PK]	87.4 PK]
76.1 MP(Fem.)]	78.6 MP(Fem.)]	86.9 LS(Fem.)]
75.0 JE]	78.5 LS(Fem.)]	86.0 JS(Fem.)]
74.7 LS(Fem.)]	77.8 JE]	85.9 BV]
72.6 BV]	75.7 BV]	85.8 MP(Fem.)]
70.8 JS(Fem.)]	72.1 JS(Fem.)]	83.9 JE]

The Newman - Keuls test of differences between means indicated that Scores within brackets did not differ significantly.

Figure 2. Mean Speaker Scores Obtained with a Carbon Microphone

the carbon microphone had the effect of accentuating the significant differences among the speakers as shown in Figure 2.

The data serve to highlight the necessity for standardizing the speakers used in intelligibility testing. They leave unanswered the question of the degree to which differences in intelligibility performance might occur in a large and diverse group of speakers that might be involved in using a military voice communications system. These tests represented a very limited sample of speakers in terms of factors such as age, regional dialects, fundamental pitch, and other factors that can be involved in speech quality. Considerable research remains to be done before it can be determined whether tests with a small group of speakers such as these provide intelligibility performance data that would be typical of a much larger population of speakers.

Variations in intelligibility performance of different speakers are presented in other contexts as shown in Figures 3 and 4, which were obtained from tests of a linear-predictive vocoder algorithm operating at 2400 bits per second (BPS). Figure 3 summarizes the effects of random bit errors superimposed on the data stream; linear regression equations were determined for the relation between overall intelligibility and the bit error rate for six male speakers. The intelligibility performance obtained for the different speakers tended to diverge as the bit error rate increased; analysis of variance confirmed that differences between slopes of the regression lines for the different speakers were highly significant ($\alpha = 0.001$). The results emphasize the hazards of using the trend in average intelligibility scores (across all speakers) for predicting intelligibility expected for any one speaker.

In Figure 4 the degradation of intelligibility caused by the speakers being located in a noise environment is summarized. In this experiment the effects of the ambient noise in the cabin of a jet aircraft were simulated by electrically mixing a recording of noise measured in the aircraft, with the recorded speech signal, prior to processing the speech with the vocoder algorithm. Intelligibility tests were performed at various signal-to-noise ratios and the resulting intelligibility data were analyzed to determine 2d order regression models relating the overall intelligibility and the signal-to-noise ratio. These data need to be interpreted with caution, since the procedure of electrically mixing the noise signal does not accurately encompass two significant effects that would be present in a "real world" situation: a speaker would alter his performance in order to try to compensate for the effect of the noise, and the frequency spectrum of the interfering noise would undergo changes due to the response of the pressure gradient microphone to a far-field source of sound. While these effects would probably alter the values shown for the regression coefficients, the results show significant differences in intelligibility for the six speakers, differences that are obscured in a single, overall intelligibility score.

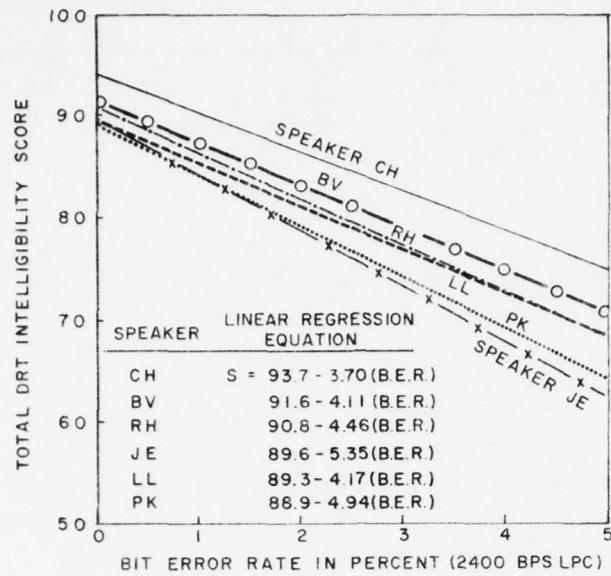


Figure 3. Total Intelligibility as a Function of Bit Error Rate for an LPC Vocoder at 2400 BPS (Six Male Speakers)

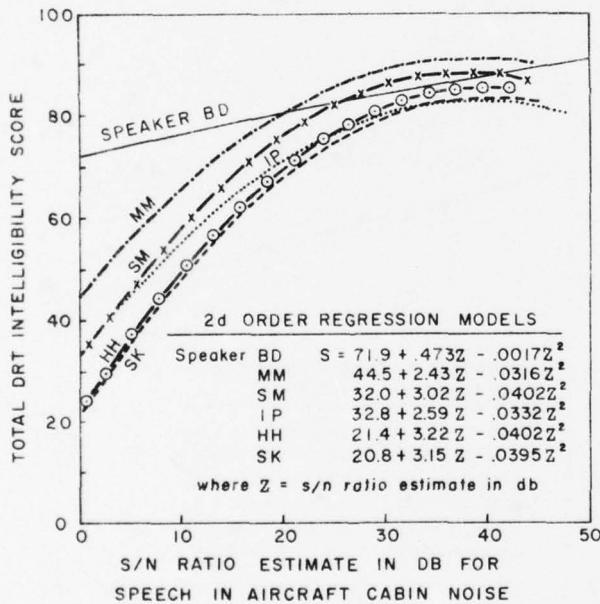


Figure 4. Total Intelligibility as a Function of Speech-to-Noise Ratio in Jet Aircraft Cabin Noise for an LPC Vocoder at 2400 BPS (Six Male Speakers)

Significant differences in intelligibility attained by different speakers, and significant speaker/processor interactions have been found to be the rule rather than the exception in speech intelligibility performance.

1.3 Phonetic Feature Variability

It has been shown by examples how large differences are found among speaker intelligibility scores. Even larger variations have been found to commonly occur among scores for the various phonetic features. Examples are presented in Figures 5 and 6 showing phonetic feature scores obtained in intelligibility performance of a linear-predictive vocoder (LPC) operating at 2400 bits per second. For these examples, separate trends are shown for the six primary phonetic features tested with the Diagnostic Rhyme Test: Voicing, Nasality, Sustention, Sibilation, Graveness, and Compactness. (It will be shown later in this report that each of these features is further subdivided by the test into four feature states, among which even larger variations occur.)

In Figure 5 linear regression lines are shown that represent the variation in intelligibility score for each of these features, in relation to the bit error rate. The spread of the regression lines serves to indicate how much deviation is

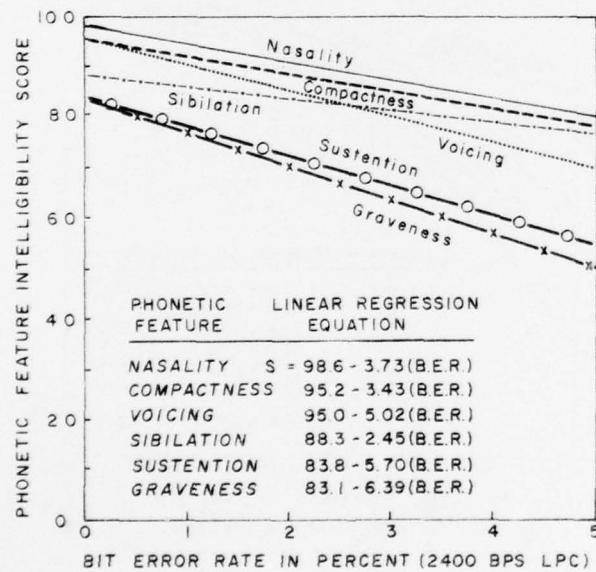


Figure 5. Phonetic Feature Intelligibility as a Function of Bit Error Rate for an LPC Vocoder at 2400 BPS

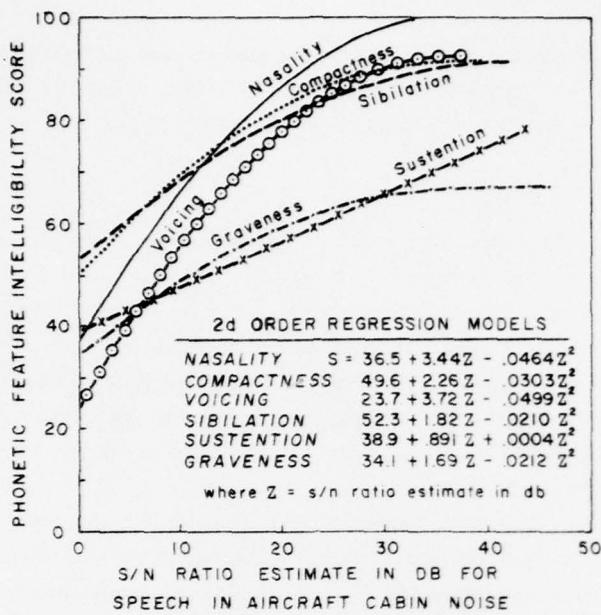


Figure 6. Phonetic Feature Intelligibility as a Function of Speech-to-Noise Ratio in Jet Aircraft Cabin Noise for an LPC Vocoder at 2400 BPS

possible with regard to the average or "total" intelligibility variation for the ensemble, as is the case in Figure 6 showing 2d order regression curves for phonetic feature intelligibility in relation to the speech-to-noise ratio estimate for speech in simulated jet aircraft cabin noise.

2. INTELLIGIBILITY THRESHOLD LEVEL (ITL) RATING

It has been shown that typically the population of intelligibility scores, the aggregate of scores representing the intelligibility of individual speaker/phonetic feature combinations, involves considerable dispersion. Perhaps because there is so much detailed information from a single multi-speaker intelligibility test, it has been the practice to condense the results to the average score and its standard error.

The proposed ITL rating involves an interpretation based on the distribution of scores obtained in a test. From analysis of the distribution, the ITL rating estimates the intelligibility value that will be equaled or exceeded by a specified percentage of the population of scores, at a specified confidence level. For example, the distribution of scores might lead to an ITL estimate that there is

95 percent probability that 80 percent of the scores (for individual speakers and phonetic features) will equal or exceed 70. (This ITL value has been observed in connection with average intelligibility scores around 90.)

2.1 Rationale for the ITL Rating

The proposed ITL rating derives from inspection of many distributions of intelligibility scores and observations of the large differences in speaker and phonetic feature scores that have been cited. It also derives from a premise that in critical military voice communications (and perhaps in other critical speech communications such as air traffic control) an intelligibility assessment is required that is made in terms of the level of performance to be expected for the majority rather than for the average: the majority of the speech events, and the majority of the speakers and listeners.

The average intelligibility scores currently used for specifying performance could be expected to state a value equaled or exceeded by half the underlying population of scores (for speakers and phonetic features) assuming that the scores were normally distributed.

However, it has been found that the populations of scores from diagnostic intelligibility tests typically are not normally distributed, but highly skewed; the higher the average score, the greater the extent to which the distribution of scores tends to be skewed.

The Lilliefors test for conformity with a normal distribution has been applied to many distributions of intelligibility data. Where the sample population is made up of the phonetic feature scores, whether of one or several speakers, the null hypothesis (for conformity with the normal distribution) has invariably been rejected.

2.2 Examples of Distributions of Speech Intelligibility Data

An example of a DRT data summary is shown in Figure 7 consisting of phonetic feature scores for a single speaker (CH) obtained with a test of continuous-variable-slope delta modulation (CVSD) at 16 kilobits per second. The numbers of listener errors (based on evaluation with a crew of eight listeners) that provided the basis for each score are shown in parentheses after each score. (A multi-speaker intelligibility test results in a set of scores such as this from each speaker of the test, plus an overall summary listing.)

The listing of Figure 7 indicates how each of the six features is tested in terms of four feature states, that is the feature Voicing involves separate, independent assessments of Voicing Present (Frictional), Voicing Present (Non-Frictional), Voicing Absent (Frictional), and Voicing Absent (Non-Frictional), these being

Diagnostic Rhyme Test Summary: CVSD 16 kbps Speaker CH

	Feature		Feature Total
	Present	Absent	
<u>Voicing</u>	98.45 (1)	98.45 (1)	98.45 (2)
Frictional	100 (0)	96.9 (1)	98.45 (1)
Non-Frictional	96.9 (1)	100 (0)	98.45 (1)
<u>Nasality</u>	100 (0)	100 (0)	100 (0)
Grave	100 (0)	100 (0)	100 (0)
Acute	100 (0)	100 (0)	100 (0)
<u>Sustention</u>	90.65 (6)	95.35 (3)	93.0 (9)
Voiced	100 (0)	96.9 (1)	98.45 (1)
Unvoiced	81.3 (6)	93.8 (2)	87.55 (8)
<u>Sibilation</u>	87.5 (8)	95.3 (3)	91.4 (11)
Voiced	78.1 (7)	90.6 (3)	84.35 (10)
Unvoiced	96.9 (1)	100 (0)	98.45 (1)
<u>Graveness</u>	71.9 (18)	78.15 (14)	75.0 (32)
Voiced	84.4 (5)	100 (0)	92.2 (5)
Unvoiced	59.4 (13)	56.3 (14)	57.85 (27)
<u>Compactness</u>	100 (0)	92.2 (5)	96.1 (5)
Voiced	100 (0)	90.6 (3)	95.3 (3)
Unvoiced	100 (0)	93.8 (2)	96.9 (2)

Total DRT Intelligibility Score: 92.325 (59)
(Nr of Listeners: 8)

Figure 7. Summary of Diagnostic Rhyme Test (DRT) Intelligibility Scores Obtained for Speaker CH with CVSD at 16 kbps

averaged four ways to obtain scores for the effects of voicing being present and absent, and for frictional and non-frictional effects of voicing. An overall average estimates the total intelligibility for voicing. These details help diagnose specific deficiencies and help in identifying possible causes and remedies.

The 24 scores for the four states of each of the six features, shown within dotted boxes in Figure 7, portray the fine details of intelligibility performance of a processor. It is among these details that the differences in voice processor performance are usually identified, and deficiencies are highlighted.

When the 24 feature-state intelligibility scores are rank-ordered and plotted in the form of a cumulative distribution, a plot of the type shown in Figure 8 results. Here each of the 24 scores is represented by a vertical line segment representing 1/24th of the data population and the ends of adjacent segments have been connected to form a cumulative distribution starting with the lowest score which in this example was for Graveness Absent (Unvoiced), the next lowest score which was for the feature state Graveness Present (Unvoiced), etc. Across the top of the figure is shown a scale corresponding to the total number of listener errors associated with each score. A normal ogive is also shown corresponding to the values of the mean (92.3) and the standard deviation (12.4) associated with

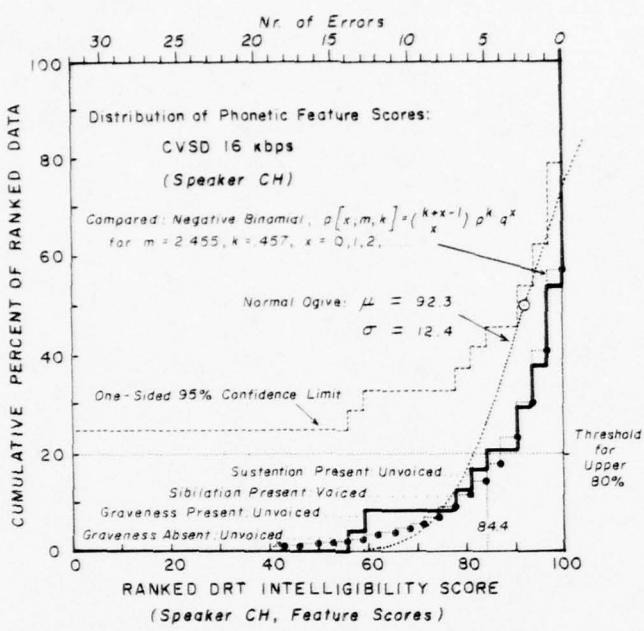


Figure 8. Distribution of Phonetic Feature Scores
Obtained for Speaker CH with CVSD at 16 kbps

this group of data. The plot indicates that 80 percent of the actual data equaled or exceeded a score of 84.4. A one-sided 95 percent confidence band for the data distribution was constructed by the method of Kolmogorov, shown as a dashed profile. The confidence limit associated with the cumulative data distribution does not intersect the dotted horizontal line defining 80 percent of the data sample; thus we are unable to make a statement about an estimated 80 percent ITL at $p = 0.95$.

This example illustrates an important feature of the ITL rating: it is assessed with respect to a confidence limit, taking into consideration the size of the sample used in arriving at the estimate. Data from a single speaker did not provide an adequate sample size for estimating the value for an 80 percent ITL at $p = 0.95$.

Also shown in Figure 8 are points representing values that result from a negative binomial probability distribution model for the distribution of listener responses in terms of listener errors, rather than conventional DRT scores. In these studies of intelligibility data distributions, comparisons were made with the normal, binomial, Poisson, and negative binomial forms. Of these, only the negative binomial probability distribution was found to provide a reasonable approximation to the speech intelligibility data distributions.

2.3 Negative Binomial Probability Distribution Model

The negative binomial probability model is summarized in Figure 9. The distribution is defined by two parameters, consisting of the mean value m (the mean number of listener errors that established feature-state scores) and a parameter k for which an estimate can be made based on the mean and variance of the data population (in units of "nrs. of errors"). These values are obtained by a simple transformation on the mean and variance values obtained from conventional scores. No adequate tables of values of the negative binomial probability distribution have been found in the literature; however, values can be readily calculated with a programmable calculator. A program for calculating negative binomial values with a Wang Model 720 Calculator is presented in Appendix B.

Figure 10 presents the distribution of scores for the feature states obtained from testing CVSD at 16 kbps, in which the data for Speaker CH presented in Figures 7 and 8 has been combined with data for eight additional speakers. Shown for comparison is a normal ogive based on the mean score (90.3) and the standard deviation (14.9) for this sample population. These values equate to $m = 3.116$ representing the average number of listener errors per feature state, and to a value of $k = 0.496$ representing the parameters for a negative binomial probability distribution model for which points are shown plotted in comparison with the data distribution.

It can be observed from the figure that 80 percent of the actual data population equaled or exceeded a value of 81.3. An ITL is shown in relation to the confidence band for the data distribution: it discloses an estimate that at $p = 0.95$, 80 percent of the data population will equal or exceed a score of 71.9. The difference between the ITL value and the actual 80 percent data value takes into consideration the sample size that was the basis for the determination.

$$\Pr[X = x] = \binom{k+x-1}{x} p^k q^x \quad x = 0, 1, 2, \dots \\ 0 < p < 1$$

$$\text{Parameters } \left\{ \begin{array}{l} E(x) = m \\ k \end{array} \right. \quad k \text{ pos.}$$

$$k^* = \left\lceil \frac{m^2}{s^2 - m} \right\rceil \quad (m = \text{Mean nr. of Errors})$$

$$p = \left(\frac{k}{m+k} \right) \quad q = \left(\frac{m}{m+k} \right)$$

Figure 9. Negative Binomial Probability Distribution Parameters

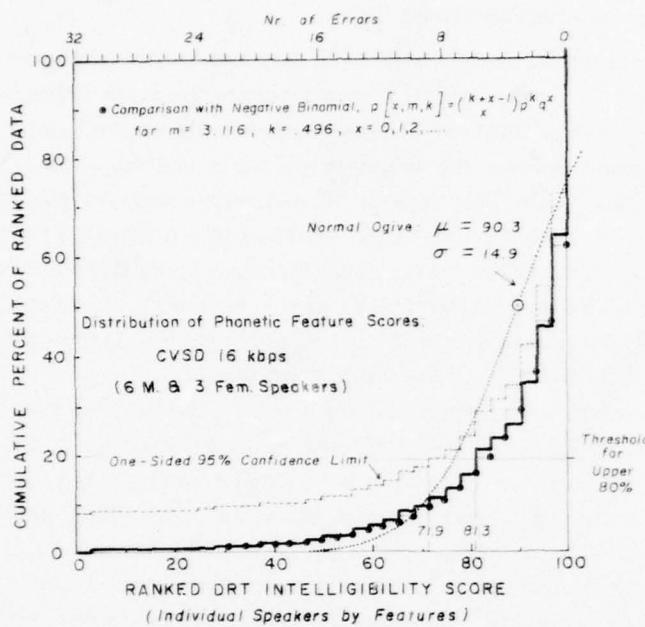


Figure 10. Distribution of Phonetic Feature Intelligibility Scores Obtained for Nine Speakers, with CVSD Processing at 16 kbps

This determination of the ITL and the resulting value obviously do not take into account the identity of the "bad" intelligibility scores that made up the bottom 20 percent of the distribution. On the other hand, in critical voice communications, poor intelligibility performance for any of the phonetic features in combination with any of the speakers presents a risk in terms of possible consequences because of messages being misunderstood, or time lost while messages are repeated. An ITL rating provides a more meaningful assessment of the degree of that risk than a conventional score specifying average intelligibility performance. The distributions of scores reveal that voice systems can have relatively high average scores and still have a significant proportion of low scores; the ITL focuses on the critical low 20 percent (in these examples) and provides information about the lower tail of the distribution of scores.

If the identity of "bad" scores is required for the purpose of guidance for research in improving intelligibility performance, or for comparing different processors, that information is readily available from conventional listings of intelligibility data.

It can be observed in Figure 10 that the negative binomial model gave good agreement with the actual data distribution. The data frequencies are compared,

with theoretical frequencies based on the negative binomial model in Table 1. A chi-squared test comparing the data and the model resulted in a value of $p = 0.395$; the null hypothesis (for conformity with a negative binomial model) was not rejected for this data obtained from testing CVSD at 16 kbps.

In Figure 11 the distribution of scores obtained from testing CVSD at 32 kbps is presented together with the 95 percent upper confidence limit for the empirical data distribution. The data indicate that there is 0.95 probability that 80 percent of the population of intelligibility scores will equal or exceed 87.5. (In the actual data, the threshold was 93.8.) The negative binomial probability model based on the parameters observed in connection with this data led to an identical ITL estimate: 87.5. The data frequencies are compared with the theoretical negative binomial model in Table 2; a chi-squared test comparing the data with the model resulted in a value of $p = 0.44$.

A third example of the distribution of intelligibility scores, from a test with nine speakers, is presented in Figure 12, representing a summary of a test of CVSD operating at 9.6 kbps. In this case the ITL was considerably lower than the two previous examples: it is estimated that at a confidence level of 0.95, 80 percent of the population of scores will equal or exceed 53.1. When the average intelligibility scores are compared for 16 kbps and 9.6 kbps CVSD, the difference was 10.2 points (90.3 vs 80.1). However, the difference in ITL values was 18.8 points (71.9 vs 53.1).

The data frequencies are compared with the theoretical negative binomial model based on the parameters derived from the data for 9.6 kbps CVSD in Table 3. Again in this case, a value of p was obtained indicating that the negative binomial probability distribution gave a reasonable approximation to the data distribution. As with the previous examples, the negative binomial model led to an identical ITL value (53.1) as obtained with the empirical data distribution.

Intelligibility data frequencies obtained from testing an LPC-10 vocoder algorithm (LPC-23*) operating at 2400 BPS, with six male speakers and two independent presentations to the listener crew are summarized in the distribution of scores presented in Figure 13. Also shown are the normal and negative binomial forms based on the parameters for this distribution and the upper one-sided 95 percent confidence belt for the empirical data distribution. From the confidence limit, an ITL estimate for this processor was obtained: there is a 95 percent probability that 80 percent of the population of intelligibility scores will equal or exceed 75.0.

Table 4 compares the data frequencies and the theoretical negative binomial frequencies based on the parameters calculated for this set of data. The value of chi-squared and corresponding value of $p = 0.098$ indicate not to reject the null hypothesis for conformity of the data distribution with the negative binomial form.

Table 1. Comparison of Intelligibility Data Frequencies and Negative Binomial Probability Distribution
 $(m = 3.116, k = 0.4962, N = 216)$

DRT Score	Nr of Listener Errors	Theoretical Probability $p(x; m, k)$	Theoretical Frequency Σp_N	Cumulative Probability Σp_N	Cumulative Frequency	Data Frequency f_s	$\frac{(f_s - p_N)^2}{p_N}$
100.00	0	.373	.80, 619	.373	.80, 619	.76	.265
96.87	1	.160	.34, 513	.533	.15, 133	.41	1.219
93.75	2	.103	.22, 716	.636	.137, 409	.25	.333
90.62	3	.074	.15, 992	.710	.153, 401	.18	.252
87.50	4	.056	.12, 059	.766	.165, 461	.6	3.044
84.37	5	.043	.9, 356	.809	.174, 818	.5	2.028
81.25	6	.034	.7, 394	.844	.182, 213	.11	1.759
78.12	7	.027	.5, 921	.871	.188, 134	.6	
75.00	8	.022	.4, 786	.893	.192, 921	.4	
71.87	9	.018	.3, 898	.911	.196, 820	.4	
68.75	10	.015	.3, 194	.926	.200, 014	.2	
65.62	11	.012	.2, 629	.938	.202, 644	.4	
62.50	12	.0101	.2, 173	.948	.204, 818	.2	
59.37	13	.0083	.1, 802	.957	.206, 621	.2	
56.25	14	.0069	.1, 499	.964	.208, 120	.3	
53.12	15	.0058	.1, 250	.969	.209, 371		
50.00	16	.0048	.1, 044	.974	.210, 415	.1	
46.87	17	.0040	.874	.978	.211, 290	.2	
43.75	18	.0034	.733	.982	.212, 024		
40.62	19	.0029	.616	.984	.212, 640		
37.50	20	.0024	.518	.987	.213, 158	1	
34.37	21	.0020	.436	.989	.213, 594		
31.25	22	.00170	.367	.991	.213, 962		
28.12	23	.00143	.310	.992	.214, 273	1	
25.00	24	.00121	.262	.993	.214, 535		
21.87	25	.00102	.221	.994	.214, 756		
18.75	26	.00086	.187	.995	.214, 944		
15.62	27	.00073	.158	.996	.215, 103		
12.50	28	.00062	.134	.9965	.215, 237		
9.37	29	.00052	.114	.9970	.215, 351		
6.25	30	.00044	.096	.9974	.215, 448		
3.12	31	.00038	.082	.9978	.215, 530	1	
0	32	.00032	.069	.9982	.215, 600		
CVSD at 16 kbps, Mean DRT Score: 90.26 S.D.: 14.902 N=216 (6M & 3Fem. Speakers)							

Table 2. Comparison of Intelligibility Data Frequencies and Negative Binomial Probability Distribution
 $(m = 1,598, k = 0,3962, N = 216)$

DRT Score	Nr of Listener Errors	Theoretical Probability $p(x; m, k)$	Theoretical Frequency p_N	$\sum p$	Cumulative Probability $\sum p_N$	Cumulative Frequency f_s	Data Frequency f_s	$\frac{(f_s - p_N)^2}{p_N}$
100.00	0	.527	113.855	.527	113.855	109	107	
96.87	1	.167	36.147	.694	150.002	44	1.706	
93.75	2	.094	20.221	.788	170.224	22	.157	
90.62	3	.060	12.943	.848	183.168	10	.669	
87.50	4	.041	8.806	.889	191.974	8		
84.37	5	.029	6.205	.917	198.179	4		
81.25	6	.021	4.472	.938	202.652	3		
78.12	7	.0152	3.214	.953	205.927	4		
75.00	8	.0112	2.426	.965	208.353	3		
71.87	9	.0084	1.813	.973	210.167	3		
68.75	10	.00632	1.365	.979	211.533	2		
65.62	11	.00478	1.034	.984	212.567	1		
62.50	12	.00364	.787	.988	213.354			
59.37	13	.00278	.601	.991	213.956			
56.25	14	.00213	.461	.993	214.417	1		
53.12	15	.00164	.354	.994	214.772			
50.00	16	.00126	.273	.996	215.046	1		
46.87	17	.00097	.211	.997	215.257			
43.75	18	.00075	.163	.997	215.421	1		

Chi-squared =
 4.798
 with 5 d.f.
 $p=.441$

CVSD at 32 kbps. Mean DRT Score: 95.01 S.D.: 8.865 N=216(6M & 3 Fem,Speakers)

Table 3. Comparison of Intelligibility Data Frequencies and Negative Binomial Probability Distribution
 $(m = 6,366, k = 0,8676, N = 216)$

DRT Score	Nr of Listener Errors	Theoretical Probability $p(x;m,k)$	Theoretical Frequency $\frac{p_N}{\sum p_N}$	Cumulative Probability $\sum p_N$	Data Frequency \bar{f}_N	Cumulative Frequency $\sum \bar{f}_N$	Data Frequency $\frac{(\bar{f}_N - \bar{f}_{N-1})^2}{\bar{f}_N}$
100.00	0	.159	.34,.305	.159	.34,.305	.48	.5,467
96.87	1	.121	.26,.193	.280	.60,.498	.29	.301
93.75	2	.100	.21,.525	.380	.82,.024	.17	.951
90.62	3	.084	.18,.107	.464	.100,.132	.9	.4,580
87.50	4	.071	.15,.403	.535	.115,.540	.10	.1,898
84.37	5	.061	.13,.201	.596	.128,.742	.15	.245
81.25	6	.0526	.11,.361	.649	.140,.104	.11	.011
78.12	7	.0454	.9,.809	.694	.149,.913	.7	.804
75.00	8	.0393	.8,.490	.733	.158,.404	.7	
71.87	9	.0341	.7,.362	.767	.165,.766	.4	.4,485
68.75	10	.0296	.6,.393	.797	.172,.159	.8	.404
65.62	11	.0257	.5,.558	.823	.177,.718	.6	.035
62.50	12	.0224	.4,.838	.845	.182,.556	.7	.966
59.37	13	.0195	.4,.214	.865	.186,.771	.3	
56.25	14	.0170	.3,.673	.882	.190,.445	.4	.100
53.12	15	.01483	.3,.204	.897	.193,.649	.6	
50.00	16	.01294	.2,.797	.909	.196,.446	.2	.666
46.87	17	.01130	.2,.442	.921	.198,.889	.2	
43.75	18	.00987	.2,.133	.931	.201,.022	.3	.039
40.62	19	.00863	.1,.864	.939	.202,.887	.3	
37.50	20	.00754	.1,.630	.947	.204,.517	.2	.649
34.37	21	.00659	.1,.425	.953	.205,.943	.3	
31.25	22	.00577	.1,.247	.959	.207,.190	.1	Chi-squared = .19,707
28.12	23	.00505	.1,.091	.964	.208,.281	.1	with 15d.f.
25.00	24	.00442	.0,.954	.969	.209,.236	.2	
21.87	25	.00387	.0,.835	.973	.210,.072	.1	
18.75	26	.00338	.0,.731	.976	.210,.804	.4	
15.62	27	.00296	.0,.641	.979	.211,.445		
12.50	28	.00259	.0,.561	.982	.212,.006		
9.37	29	.00227	.0,.491	.984	.212,.498		
3.12	31	.00174	.0,.377	.988	.213,.307	.1	
(-28,1)						.001	
CVSD at 9.6 kbps. Mean DRT Score: 80.11 S.D.: 22.77 N=216 (6M & 3Fem. Speakers)						1	

Table 4. Comparison of Intelligibility Data Frequencies and Negative Binomial Probability Distribution
 $(m = 3,501, k = 0, 7274, N = 288)$

DRT Score	Nr of Listener Errors	Theoretical Probability $p(x; m, k)$	Theoretical Frequency $\frac{pN}{\sum p}$	Cumulative Probability $\sum p$	Cumulative Frequency $\sum f_N$	Data Frequency f_s	Data Frequency $\frac{(f_s - pN)^2}{pN}$
100,00	0	.278	.80,054	.278	.80,054	.89	1,000
96,87	1	.167	.48,213	.445	.128,267	.48	.001
93,75	2	.120	.34,477	.565	.162,745	.27	1,622
90,62	3	.090	.25,952	.655	.188,697	.28	.162
87,50	4	.070	.20,023	.725	.208,720	.15	1,260
84,37	5	.054	.15,674	.779	.224,395	.8	3,757
81,25	6	.043	.12,388	.822	.236,783	.17	1,717
78,12	7	.034	.9,857	.850	.246,641	.11	.133
75,00	8	.027	.7,883	.884	.254,525	.10	.569
71,87	9	.022	.6,329	.906	.260,855	.5	
68,75	10	.018	.5,097	.923	.265,953	.3	1,027
65,62	11	.014	.4,116	.938	.270,069	.8	3,665
62,50	12	.012	.3,330	.949	.273,400	.5	
59,37	13	.009	.2,699	.959	.276,100	.4	
56,25	14	.008	.2,191	.966	.278,292	.2	
53,12	15	.006	.1,781	.972	.280,073		
50,00	16	.0050	.1,450	.978	.281,524	.1	
46,87	17	.0041	.1,181	.982	.282,705		
43,75	18	.0033	.963	.985	.283,669	.2	
40,62	19	.0027	.786	.988	.284,455	.2	
37,50	20	.0022	.642	.990	.285,097		
34,37	21	.00182	.524	.992	.285,622	.1	
31,25	22	.00148	.429	.993	.286,051		
28,12	23	.00121	.351	.994	.286,402	.1	
25,00	24	.00099	.287	.995	.286,689		
21,87	25	.00081	.235	.996	.286,924	.1	

LPC-10 Vocoder Algorithm (LPC-23*) at 2400 BPS. Mean DRT Score: 89,06
 Standard Deviation: 14,10 N = 288 (Six Male Speakers, two presentations)

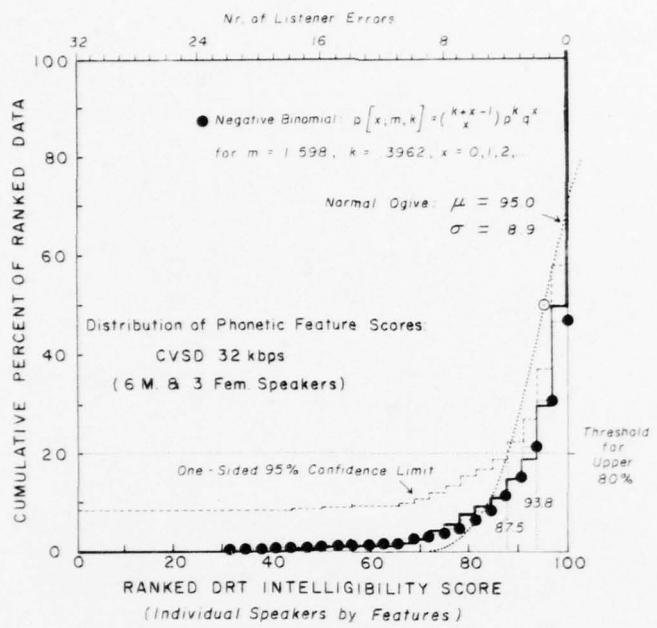


Figure 11. Distribution of Phonetic Feature Intelligibility Scores Obtained for Nine Speakers with CVSD Processing at 32 kbps

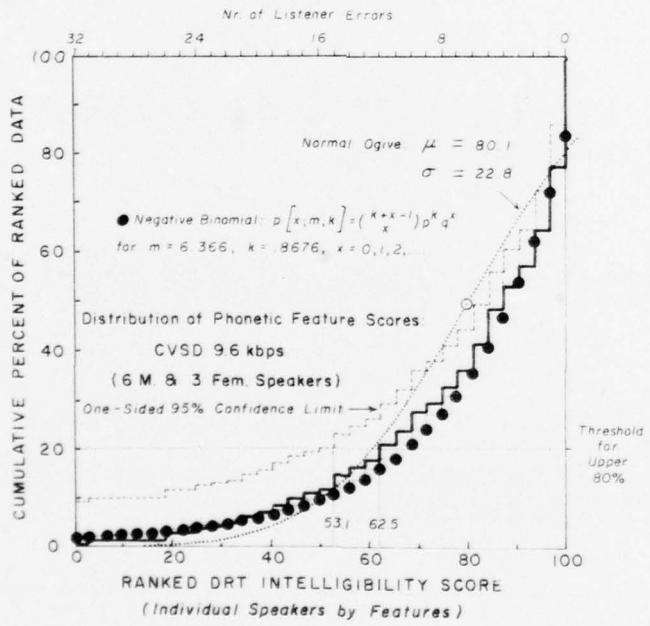


Figure 12. Distribution of Phonetic Feature Intelligibility Scores Obtained for Nine Speakers with CVSD Processing at 9.6 kbps

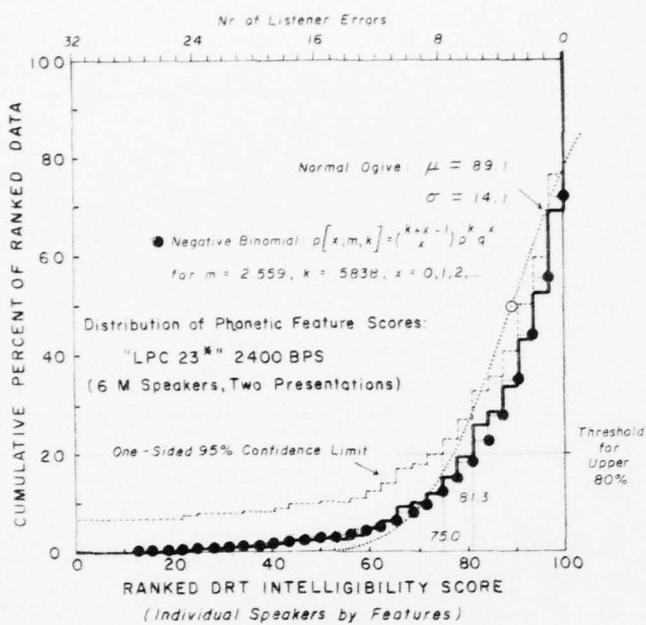


Figure 13. Distribution of Phonetic Feature Intelligibility Scores Obtained for Six Speakers (Two Presentations) with an LPC Vocoder

The intelligibility threshold level (ITL) estimate calculated with the theoretical cumulative probability associated with the negative binomial model resulted in an identical value (75.0) as that obtained from the empirical data distribution.

An example based on intelligibility data obtained with another type of voice processor, a sixteen-channel vocoder operating at 2400 BPS tested with six male and three female speakers, is presented in Figure 14. Comparing the data distribution for the LPC-10 vocoder algorithm (Figure 13) illustrates again that differences in ITL ratings tend to be greater than those observed for mean intelligibility scores. The channel vocoder, with a mean score of 83.0, was approximately six points lower than the mean intelligibility score obtained for the LPC-10 vocoder algorithm. However, the difference in ITL ratings for the two processors was more than 15 points (75.0 vs. 59.4).

The values associated with the data and the negative binomial model are listed in Table 5, together with the results of a chi-squared test comparing the empirical data frequencies and the negative binomial model. In this case, the value of p was 0.025, and the null hypothesis was rejected. Although the data represented a poor fit to the negative binomial form, the ITL calculated from the negative binomial model differed by only one quantum level in the data (ITL of 62.5 from the model vs. 59.4 from the actual data distribution).

Table 5. Comparison of Intelligibility Data Frequencies and Negative Binomial Probability Distribution
 $(m = 5.455, k = 0.9910, N = 216)$.

DRT Score	Nr of Listener Errors	Theoretical Probability $p(x; m, k)$	Theoretical Frequency p_N	Theoretical Frequency p	Cumulative Probability p_N	Cumulative Frequency f_s	Data Frequency f_s	$\frac{(f_s - p_N)^2}{p_N}$
100.00	0	.156	33.771	.156	33.771	.49	.49	6.868
96.87	1	.131	28.321	.287	62.093	.24	.24	.659
93.75	2	.110	23.859	.398	85.952	.14	.14	4.074
90.62	3	.093	20.130	.491	106.083	.17	.17	4.487
87.50	4	.079	16.997	.570	123.081	.13	.13	.940
84.37	5	.066	14.358	.636	137.440	.15	.15	.029
81.25	6	.0562	12.133	.692	149.573	.9	.9	.809
78.12	7	.0475	10.254	.740	159.827	.15	.15	2.197
75.00	8	.0401	8.668	.780	168.496	.16	.16	.205
71.87	9	.0339	7.328	.814	175.824	.13	.13	.390
68.75	10	.0287	6.196	.843	182.021	.3	.3	
65.62	11	.0243	5.239	.867	187.260	.3	.3	2.583
62.50	12	.0205	4.430	.887	191.691	.5	.5	.073
59.37	13	.0173	3.747	.905	195.438	.6	.6	
56.25	14	.0147	3.168	.919	198.607	.1	.1	.001
53.12	15	.0124	2.680	.932	201.287	.3	.3	
50.00	16	.0105	2.266	.942	203.554	.2	.2	.001
46.87	17	.00887	1.917	.951	205.472	.3	.3	
43.75	18	.00750	1.621	.959	207.093	1	1	
40.62	19	.00635	1.371	.965	208.465	1	1	
37.50	20	.00537	1.160	.970	209.626	1	1	
34.37	21	.00454	.981	.975	210.607			
31.25	22	.00384	.830	.979	211.438	5	5	Chi-Squared=
28.12	23	.00325	.702	.982	212.140	1	1	24.733
25.00	24	.00275	.594	.985	212.735			with 13 d.f.
21.87	25	.00232	.502	.987	213.237			
18.75	26	.00196	.425	.989	213.663			
15.62	27	.00166	.339	.991	214.022	1	1	
12.50	28	.00140	.204	.992	214.327			
9.37	29	.00119	.257	.993	214.584			
6.25	30	.00100	.217	.994	214.802			
3.12	31	.00085	.184	.995	214.986			
0	32	.00072	.155	.996	215.142			
-3.12	33	.00061	.131	.997	215.274	1	1	

Sixteen-Channel Vocoder at 2400 BPS. Mean DRT Score: 82.95 S.D.: 18.62
 $N = 216$ (Six Male & three Female Speakers)

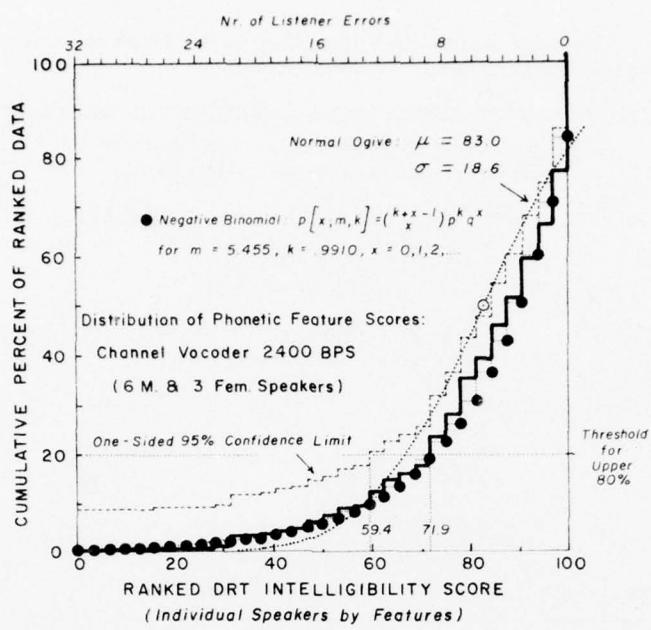


Figure 14. Distribution of Phonetic Feature Intelligibility Scores Obtained for Nine Speakers with a Sixteen-Channel Vocoder at 2400 BPS

2.4 Results of Chi-Squared Tests for Conformity of Intelligibility Data Distributions with Negative Binomial Probability Model

To further test conformity of intelligibility data distributions with a negative binomial probability model, a series of chi-squared tests were performed comparing empirical data distributions with the negative binomial probability model on 81 sets of speech intelligibility data on hand from prior tests and evaluations of various speech processor algorithms and hardware. These tests included data from the combinations of speakers and processors summarized in Table 6, ranging from data for a single speaker (both male and female speakers) to as many as twelve male speakers, the processors including LPC and channel vocoders and CVSD at three data rates. Intelligibility data were analyzed separately for voiced and unvoiced feature data as well as total data summaries. The results of this exploratory study are summarized in Figure 15 which presents the distribution of the values of probability based on the values of chi-squared in conjunction with the degrees of freedom. Almost one-fourth of the 81 cases resulted in values of p less than 0.05, for which the null hypothesis would be rejected. Thus the agreement with the negative binomial probability model was far from perfect. Many of

Table 6. Summary of Intelligibility Data Sets Tested for Conformity with the Negative Binomial Probability Model

DRT Intelligibility Data Tested for Conformity with the Negative Binomial Distribution	
Talkers:	Single Speaker (M;Fem) Three-Speaker (3 M; 3 Fem) Six M. Speakers (two versions) Nine Speakers (6 M, 3 Fem) Twelve M. Speakers
Processing:	LPC Vocoders; Channel Vocoders; APC; CVSD (3 rates); Hybrid Vocoders.
NR of Listeners:	Eight
Data Sets:	Feature scores (by individual speakers) -Voiced features -Unvoiced features -All features Total DRT scores (by listeners/speakers)
Total Data Groups Used for Chi-Squared Tests:	81

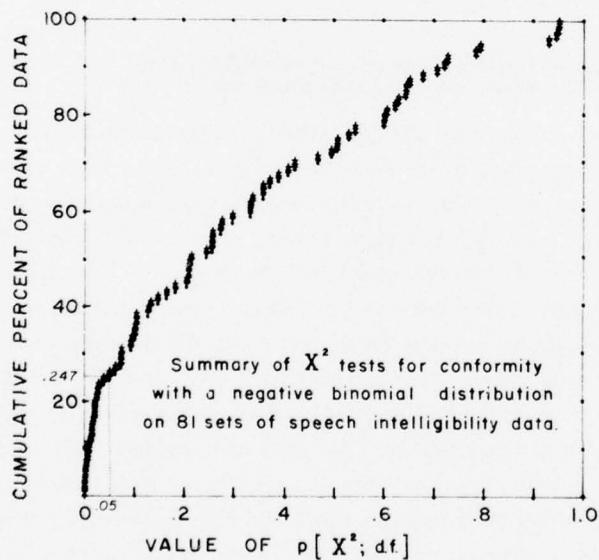


Figure 15. Summary of Chi-Squared Tests for Conformity of Speech Intelligibility Data Distributions with a Negative Binomial Probability Model

Table 7. Deviations in Conformity with the Negative Binomial Probability Model Found with Reception of Listening Tests

Processor	Test Nr.	Date of Presentation	DRT			Negative Binomial Model		d.f.	$p(X^2, d.f.)$
			Mean	Standard Deviation	m	k	χ^2		
LPC	#2050	26 Apr	90.58	13.31	3.015	.6014	9.603	7	.212
		27 May	91.25	11.97	2.799	.6603	17.742	7	.013*
LPC at 1% BER	#2051	29 Apr	85.22	16.62	4.730	.9498	13.849	9	.128
		27 May	86.74	14.95	4.244	.9668	19.535	9	.021*
PLPC	#2043	8 April	92.16	12.39	2.508	.4760	6.790	7	.451
		20 May	92.62	11.269	2.362	.5241	9.549	7	.216
PLPC at 1% BER	#2047	22 April	87.65	13.661	3.952	1.031	7.139	7	.415
		29 April	88.37	14.191	3.723	.8201	17.523	9	.041*
LPC at 3% BER	#2052	6 May	76.65	20.62	7.473	1.549	17.657	13	.171
		13 May	77.52	19.47	7.195	1.637	16.928	13	.203
LPC at 5% BER	#2053	6 May	68.79	23.06	9.987	2.244	11.637	12	.475
		13 May	68.31	24.38	10.140	2.028	20.686	16	.191
PLPC at 3% BER	#2048	22 April	79.79	19.26	8.466	1.3272	11.100	12	.520
		20 May	81.36	19.15	5.966	1.1267	5.298	11	.916
PLPC at 5% BER	#2049	22 April	70.46	22.04	9.452	2.2175	16.467	13	.225
		20 May	71.89	22.09	8.994	1.9743	25.365	14	.031*
LPC with "new" speakers	#2069	21 July	88.56	14.61	3.660	.7361	7.547	8	.479
		4 Aug	89.67	13.56	3.306	.7042	12.276	9	.198
		1 Sept	89.71	14.11	3.292	.6345	13.318	7	.065

the data sets represented composite results from two separate presentations to the listener crews. It was subsequently found that a curious trend was present in the data sets in which the composite data (for two or more presentations to listeners) showed poorer agreement with the model; data from the first presentation to listeners agreed with the negative binomial model in all of these cases. Further details of this anomaly are discussed in the following section.

A comparison of ITL values obtained from the cumulative data distributions, and ITL's obtained with the use of the negative binomial probability model, showed good agreement, even for data sets that deviated significantly from the model.

2.5 Phenomenon Observed in Connection with Replication of Listening Tests

In the speech intelligibility data analyzed for conformity with the negative binomial probability model many of the data sets represented composite results of presentation of the DRT recordings to the listener crew on two separate occasions a week or more apart; one set of data involved three presentations at intervals of a month. The initial chi-squared tests reported in the previous section were performed on composite data combined over all presentations of a particular DRT recording. Subsequently in the studies, separate assessments were made for the data resulting from each separate presentation to listeners. A pattern was found in the results: agreement of the intelligibility data with the negative binomial form was almost always higher for the first presentation to listeners, than for subsequent presentations. These findings are presented in Table 7.

The listener tests were performed "blind," that is, the listening crew had no knowledge as to the identity of any particular speech processor or the processing conditions. Any given test was always interspersed with other tests in a random manner. The listeners had much prior experience with these scramblings of the DRT word lists, and while there was a slight tendency for scores to increase at the second presentation, in most instances the change was not statistically significant.

Because of these considerations it is difficult to conceive any explanation as to why the intelligibility data distributions tended to show increasing deviation from the negative binomial probability form with the second and subsequent presentations.

3. DETERMINATION OF INTELLIGIBILITY THRESHOLD LEVELS (ITL's)

It was established that the distributions of diagnostic intelligibility scores were sufficiently close to the negative binomial probability model that two alternative procedures for determining ITL's were available.

3.1 Determination of ITL's from Cumulative Data Distributions

In this procedure the sample population of diagnostic intelligibility scores is rank-ordered, and the ranked data are utilized in constructing a cumulative table of scores in relation to cumulative percentiles of the data population. In these studies a program was written for the Wang Model 720 Calculator to perform the ranking. Data values were entered into an auxiliary memory via the calculator keyboard, and a program subsequently rearranged the table in rank-order. Each datum was paired with a code number to maintain identification of the phonetic feature and speaker associated with each value.

A confidence band for the distribution was established by the method of Kolmogorov, in which a one-sided confidence band is defined by a simple offset of population percentiles by an appropriate quantile that is a function of the value of p and the sample size. Kolmogorov's method assumes a random sample X_1, X_2, \dots, X_n of size n associated with some unknown distribution function $F(x)$. For the confidence coefficient to be exact, the method requires that the samples are from a continuous distribution; however, if the random variables are discrete (as in this case) the confidence band is conservative, that is, the "true" but unknown confidence coefficient is greater than the stated one.

Kolmogorov's method is most readily used by constructing a tabular listing or a graphical representation of the empirical distribution function. In a graphical representation, as in Figures 8 and 9 and the examples in Appendix A, each datum can be considered as a vertical segment that establishes $100/n$ percent of the total population; end points of adjacent segments are joined to form the distribution function $S(x)$ which is terminated at zero and 100 percent of the sample. A tabular listing as in Table 4 can be utilized for listing cumulative percentiles representing the end points or boundaries of each segment (datum).

A confidence band with confidence coefficient $1-a$ is created with the use of the $1-a$ quantile from a table of the Kolmogorov test statistic (Appendix D). In determining ITL's, the upper one-sided confidence band is of interest, which is formed by vertical displacement of the empirical distribution function graph by the value of Q_{1-a} from a table of the Kolmogorov test statistic. Thus the confidence boundary is an exact replica of the empirical distribution, offset by an appropriate amount, and terminated at the values Q_{1-a} and 100 percent illustrated in the examples of Figures 8 and 9. Alternatively, the value of Q_{1-a} is added (or subtracted for a lower one-sided limit) from the cumulative percentiles of the tabular listing. If the confidence limit is denoted by $U(x)$,

$$U(x) = S(x) + Q_{1-a}$$

forming the boundary of a one-sided 1-a confidence band which completely contains the "true" $F(x)$.

Values for ITL's for various percentages of the data population are determined in relation to the upper one-sided confidence limit, either graphically as illustrated in Figure 9, or with more accuracy from a tabular listing as in the example of Table 4.

Diagnostic intelligibility data populations presented here involved 24 intelligibility scores (for the phonetic feature states) from each of the speakers in an intelligibility test. With two and more speakers, the number of samples exceeded 40, and the approximation for calculating the one-sided quantile of the Kolmogorov test statistic at $p = 0.95$ was used:

$$For n > 40,$$

$$Q_{0.95} = 1.22/\sqrt{n}$$

3.2 Determination of ITL's from a Negative Binomial Probability Model

After a mean DRT score and its variance have been determined for a set of intelligibility data, conversions to parameters m and k that characterize a negative binomial probability model are as follows:

$$\text{Mean nr. of listener errors} = m = (100 - \bar{D})/3.125$$

where \bar{D} = mean DRT score

$$\text{Listener error variance} = s_e^2 = S_D^2/(3.125)^2$$

where S_D^2 = DRT score variance

$$\text{Estimate of } k = k^* = \left| \frac{m^2}{s_e^2 - m} \right|$$

Here is an example of the derivations for the data of Figure 9 and Table 1, from intelligibility data from testing CVSD at 16 kbps with nine speakers.

$$\text{Mean DRT score} = \bar{D} = 90.26 \quad \text{DRT score variance} = S_D^2 = 222.06 \quad n = 216$$

Consequently

$$m = \frac{100 - 90.26}{3.125} = 3.12 \text{ (mean listener errors per score)}$$

$$s_e^2 = \frac{222.06}{(3.125)^2} = 22.74 \text{ (listener error variance)}$$

leading to the estimate for k:

$$k^* = \frac{(3.12)^2}{22.74 - 3.12} = 0.496$$

Using these values in calculating probabilities based on a negative binomial distribution:

$$p = \frac{k}{m+k} = 0.137 \quad p^k = 0.373 = \text{probability of no errors}$$

$$q = \frac{m}{m+k} = 0.863$$

$$\begin{aligned} p[x; k, m] &= \binom{x+k-1}{x} p^k q^x \quad x = \text{nr of errors} = 0, 1, 2, \dots \\ &= \binom{x-0.504}{x} (0.3731) (0.863)^x \end{aligned}$$

resulting in the probability values and distribution function presented in Table 1.

A confidence band for the negative binomial distribution function can be formed with the same Kolmogorov test statistic and procedure used with the empirical data distributions; the Kolmogorov test statistic is valid without regard to the form of the distribution. Thus a confidence band for the negative binomial distribution function is formed by a displacement of the percentiles associated with the distribution function by an appropriate value of Q_{1-a} for the Kolmogorov test statistic.

A number of intelligibility data distributions are shown in Appendix A, together with 95 percent one-sided confidence bands and ITL values.

4. INTELLIGIBILITY THRESHOLD LEVEL (ITL) RATINGS FOR SOME VOICE PROCESSORS

Conventional intelligibility scores are compared with ITL values in Tables 8, 9, and 10, and illustrate that differences in intelligibility scores usually become magnified in differences in ITL's for the same intelligibility data. The data also illustrate that typically there are large differences between the intelligibility scores

Table 8. Intelligibility Threshold Level (ITL) Ratings for LPC Vocoder Algorithms Operating with Random Bit Errors

Effects of Random Bit Errors on Serial 2400 BPS Linear Predictive Vocoders				
based on six male speakers and two presentations to eight listeners				
Test Configuration	Mean Score	80% Intelligibility Threshold Level ($p = 0.95$)*		
		Voiced	Unvoiced	Total
LPC Vocoder				
Zero BER	90.9	81.3	68.8	75.0
1%	86.0	68.8	53.1	65.6
3%	77.1	53.1	40.6	53.1
5%	68.6	40.6	31.3	40.6
Piecewise-LPC Vocoder				
Zero BER	92.4	78.1	71.9	78.1
1%	88.0	71.9	65.6	71.9
3%	80.6	62.5	43.8	62.5
5%	71.2	50.0	31.3	43.8

*There is 95% Confidence that 80% of the specified population of diagnostic intelligibility scores (feature scores, by Speakers) will equal or exceed the stated value.

Table 9. Comparisons of Conventional Intelligibility Scores and ITL's from Diagnostic Rhyme Test Scores, 6 Male and 3 Female Speakers and 8 Listeners

Processor	Mean Score	80% Intelligibility Threshold Level (95% Confidence)*		
		Voiced	Unvoiced	Total
CVSD 9.6 kbps	80.1	62.5	25.0	53.1
CVSD 16 kbps	90.3	81.3	56.3	71.9
CVSD 32 kbps	95.0	90.6	71.9	87.5
Ch. Vocoder 2400	83.0	62.5	37.5	59.4

*There is 95% confidence that 80% of the population of diagnostic intelligibility scores (feature scores, by speakers) will equal or exceed the stated value.

Table 10. Comparisons of ITL's Derived from Empirical Data Distributions, and Obtained with the Negative Binomial Probability Model

Comparison of 80% ITL's ($p = 0.95$)						
Values from data distribution, vs. Negative Binomial model						
(Data from 6 M. & 3 Fem. Speakers, 8 Listeners)						
Voiced Features		Unvoiced		Total		
Processor	Data	(Model)	Data	(Model)	Data	(Model)
CVSD 9.6 kbps	62.5	(65.6)	25.0	(28.1)	53.1	(53.1)
CVSD 16 kbps	81.3	(81.3)	56.3	(53.1)	71.9	(75.0)
CVSD 32 kbps	90.6	(90.6)	71.9	(71.9)	87.5	(87.5)
Ch. Voc. 2400	62.5	(65.6)	37.5	(40.6)	59.4	(62.5)
Ch. Voc. 2400	65.6	(65.6)	56.3	(56.3)	65.6	(65.6)
APC-4 6400	68.8	(68.8)	40.6	(40.6)	59.4	(62.5)

for the voiced and for the unvoiced speech sounds, in comparison with the total ensemble, and highlight the fact that the greatest potential payoff in improving speech intelligibility will come through improving the fidelity of the unvoiced speech events.

In Table 8, two linear-predictive (LPC) vocoder algorithms are compared in terms of their intelligibility performance in the presence of random bit errors as could be caused by interference or low-grade transmission channels, when no measures are provided for error protection.

Table 9 compares conventional intelligibility scores and ITL's for continuous variable-slope delta modulation (CVSD) at three data rates, and a conventional channel vocoder.

Table 10 compares the ITL's obtained from the empirical data distribution with the values obtained with the use of the negative binomial probability model. The greatest discrepancy in ITL values was a one-quantum change in the value (3.125 points); over half of these eighteen comparisons gave perfect agreement in ITL values assessed by the two methods.

5. CONCLUSIONS AND RECOMMENDATIONS

Intelligibility scores for voice processors have been found to be typically characterized by highly significant differences among speakers, as well as highly significant differences among scores for the various phonetic features.

Distributions of intelligibility scores are not normally distributed, but highly skewed.

A negative binomial probability distribution was found to give good agreement with empirical intelligibility data distributions.

A new performance rating for voice communications devices, termed an Intelligibility Threshold Level (ITL), was conceived as a means of taking these findings into consideration in establishing a measure of performance that is an estimate of an intelligibility value that the majority (rather than the simple average) of intelligibility scores for a voice processor will equal or exceed, at a specified confidence level established in relation to the sample size used in obtaining the rating.

It is proposed that an ITL rating is a more meaningful assessment of the degree of risk involved in misunderstanding voice messages, or causing time to be lost in requiring messages to be repeated.

It was shown that ITL's can be determined by two alternative methods: by rank-ordering the intelligibility scores for a voice processor and constructing the cumulative distribution of data and its confidence band, or by using a negative binomial probability model for the distribution.

Chi-squared tests indicated that in most cases the negative binomial probability model gave a reasonable approximation to the data distribution.

Intelligibility Threshold Levels (ITL's) estimated with the negative binomial model differed by at most one quantum value (3.125) from ITL's determined from the empirical distributions.

It is recommended that future speech intelligibility tests and evaluations of digital voice communications processors and systems include a determination of the 80 percent ITL's at 0.95 probability, that is determine the intelligibility level for which there is a 95 percent probability that 80 percent of the population of intelligibility scores (for individual speakers and phonetic features) will equal or exceed.

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Appendix A

Voice Processor Intelligibility Data Distributions and
Intelligibility Threshold Levels (ITL's)

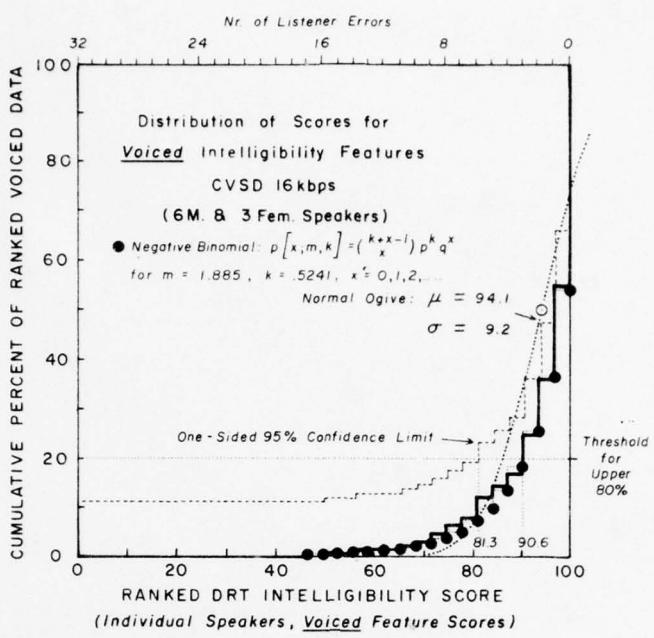


Figure A1.a. CVSD at 16 kbps: Voiced Intelligibility Features

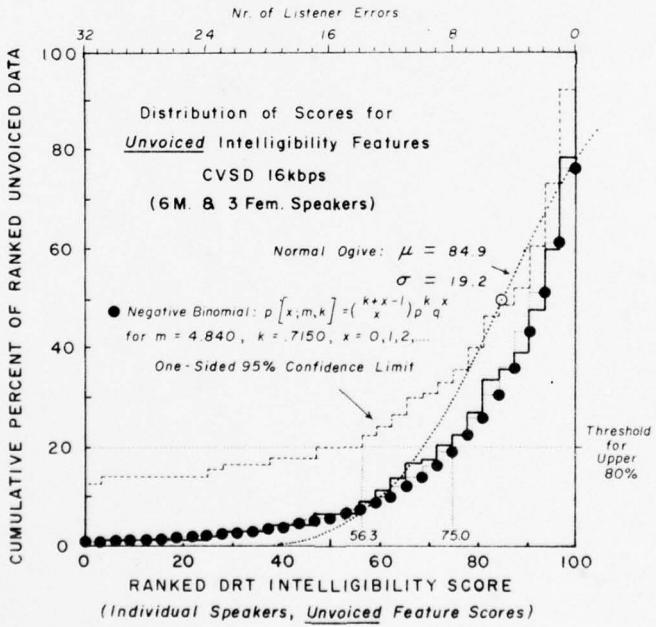


Figure A1.b. CVSD at 16 kbps: Unvoiced Intelligibility Features

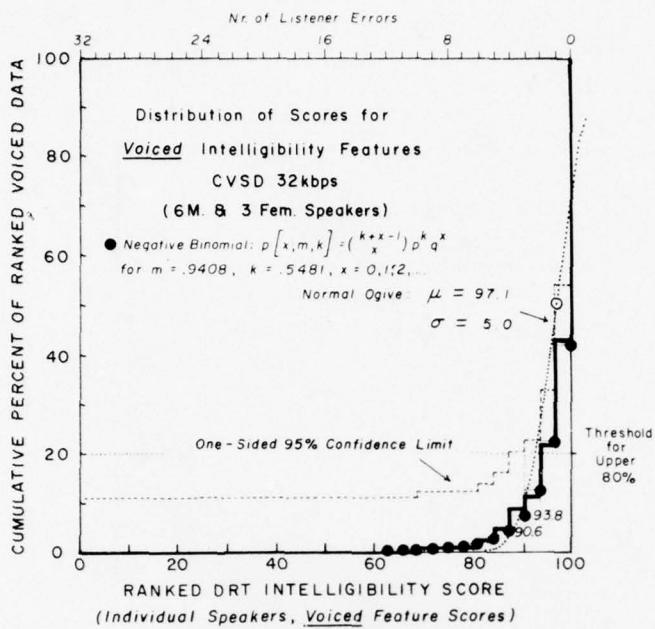


Figure A2.a. CVSD at 32 kbps: Voiced Intelligibility Features

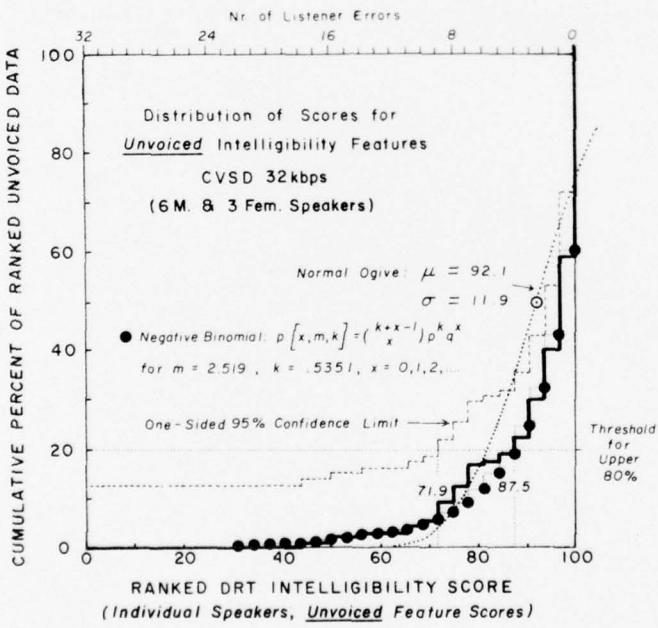


Figure A2.b. CVSD at 32 kbps: Unvoiced Intelligibility Features

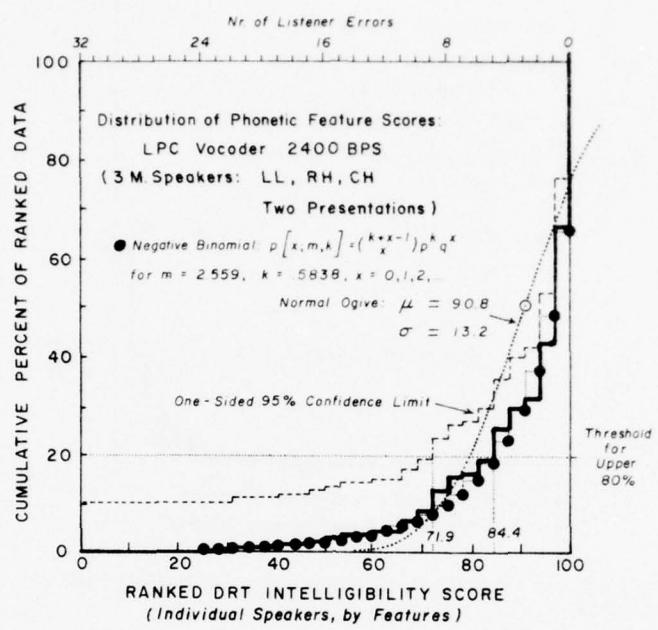


Figure A3. LPC Vocoder at 2400 BPS: Three Male Speakers (LL, RH, CH)

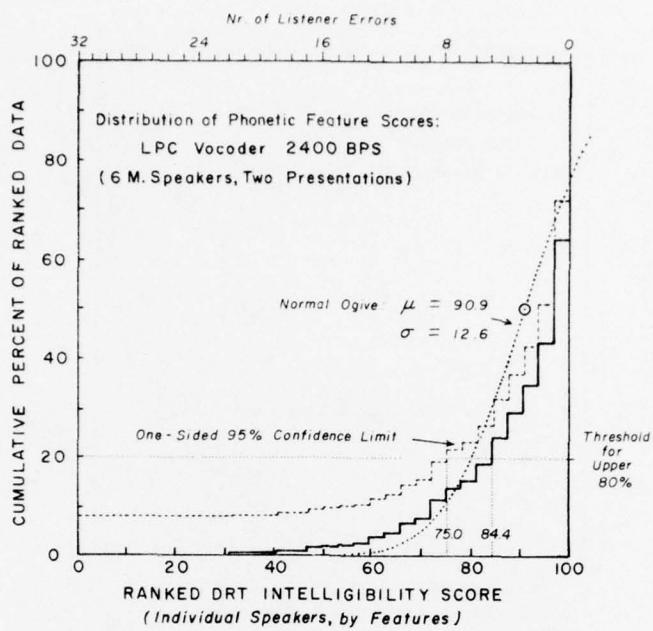


Figure A4.a. LPC Vocoder at 2400 BPS: Six Male Speakers

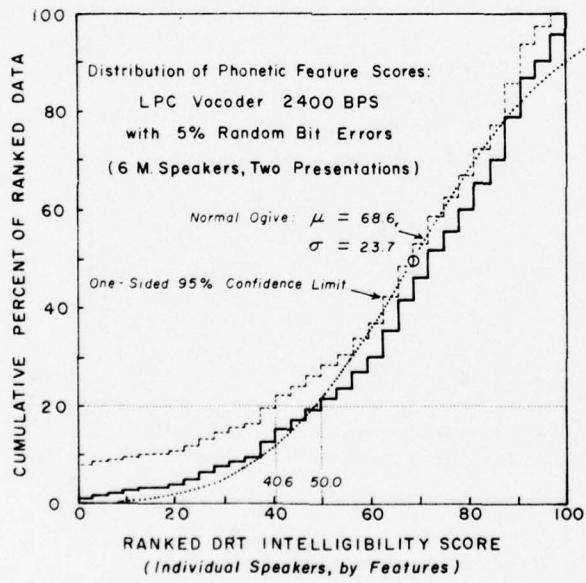


Figure A4.b. LPC Vocoder at 2400 BPS with 5 Percent Random Bit Errors (Six Male Speakers)

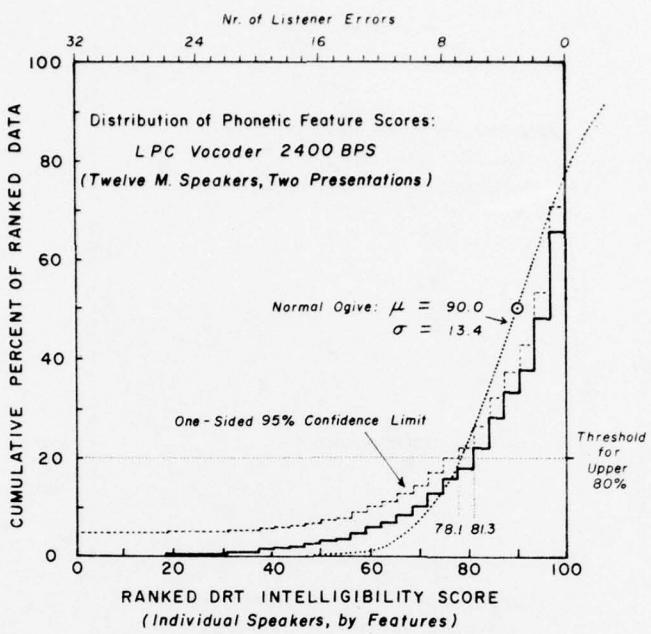


Figure A5.a. LPC Vocoder at 2400 BPS: Twelve Male Speakers

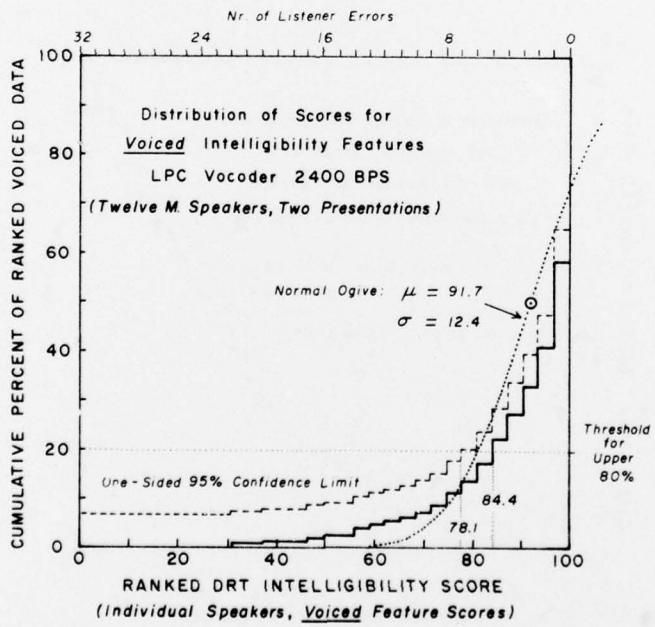


Figure A5.b. LPC Vocoder at 2400 BPS: Voiced Intelligibility Features (Twelve Male Speakers)

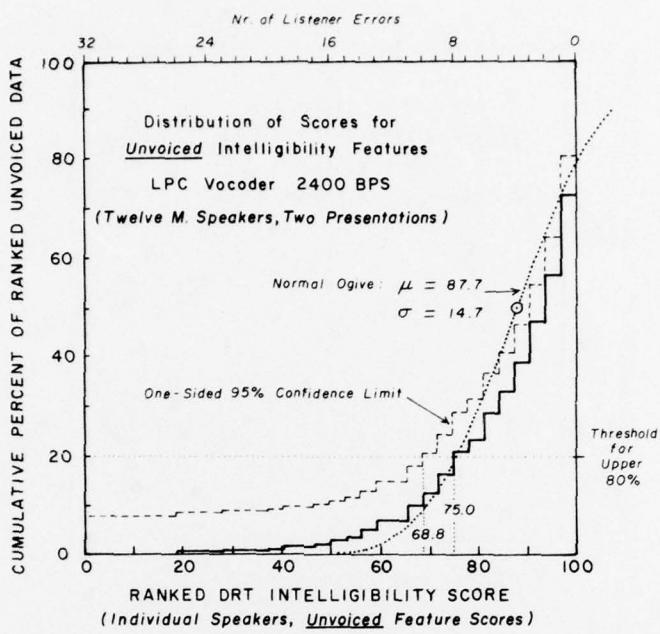


Figure A5.c. LPC Vocoder at 2400 BPS: Unvoiced Intelligibility Features (Twelve Male Speakers)

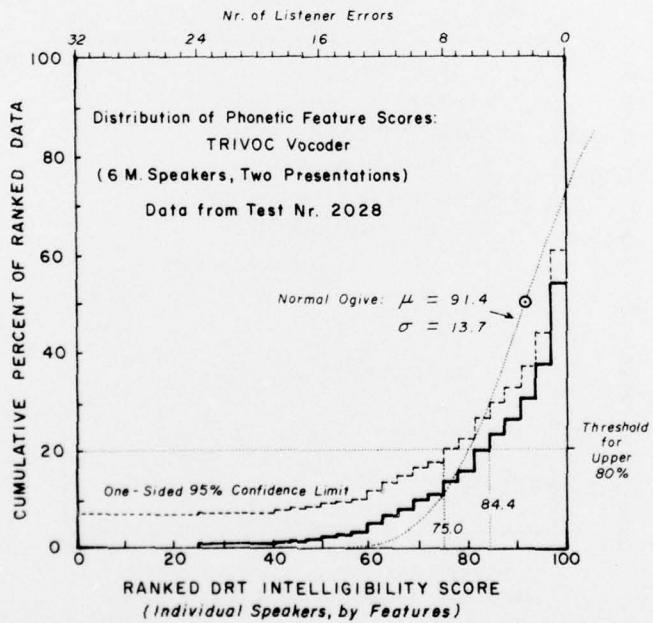


Figure A6.a. TRIVOC Vocoder at 2400 BPS: Six Male Speakers

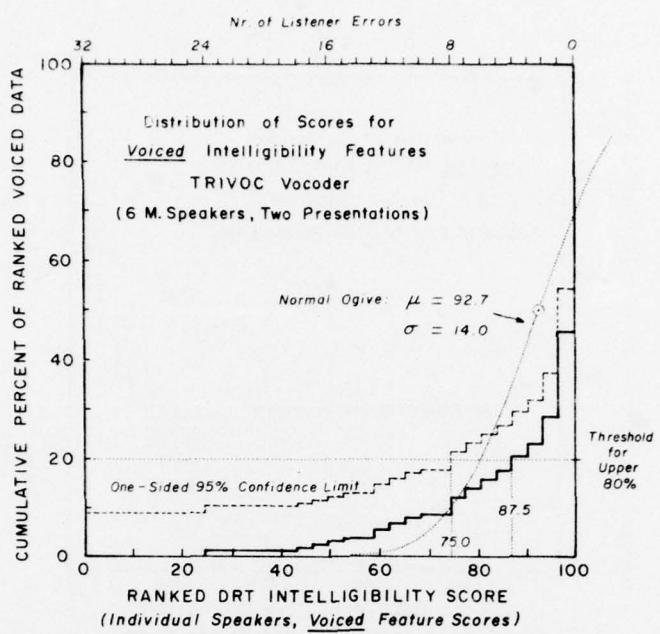


Figure A6.b. TRIVOC Vocoder at 2400 BPS: Voiced Intelligibility Features, (Six Male Speakers)

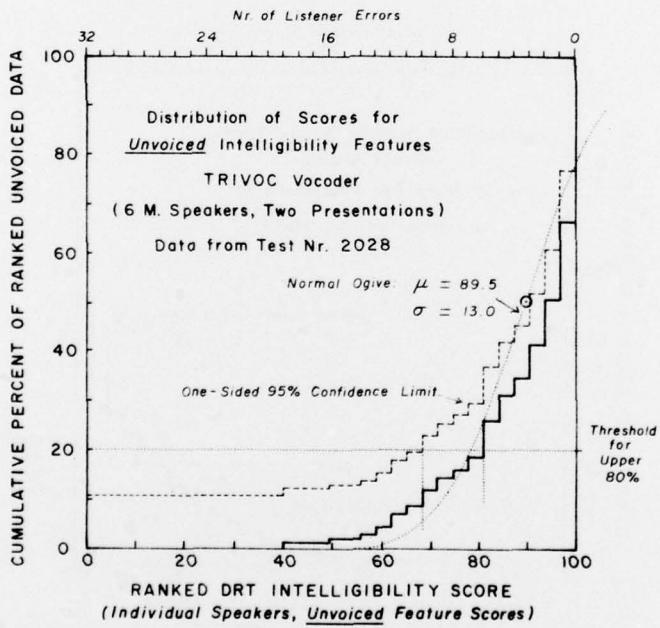


Figure A6.c. TRIVOC Vocoder at 2400 BPS: Unvoiced Intelligibility Features, (Six Male Speakers)

Appendix B

Wang Model 720 Calculator Program for Negative Binomial Probability Distribution

This program sequence is designed to operate in conjunction with some utility subroutines for storing and retrieving the contents of the calculator x&y registers, and for calculating and executing plots in conjunction with the Wang Model 702 Printer/Plotter.

To initialize, values of m, s, n, and the constant for converting between listener errors and DRT score, are entered from the keyboard as follows:

```
m into register 006.  
s (standard deviation in listener errors) into reg. 044  
n into register 002  
c (for converting error count to DRT score) into reg 001
```

Load a zero into reg 032 to obtain a listing.
Load a 2 into reg 032 to obtain a plot.

Position the Model 702 Plotter Printer at the top of the page for a listing; at the origin for a plot.

Execute "Search 1515".

Wang Calculator Program - continued.

0408	MARK	Start Neg.	0415	recall y
1515	1515	Binomial Routine	0003	003 ln (p)
0700	0		0405	recall dir
0404	store dir		0001	001 k*
0008	008		0602	multiply
0405	recall dir		0414	store y
0404	044 s		0011	011
0713	square		0405	recall dir
0604	↑		0012	012 Xi
0405	recall dir		0412	Write A Skip if
0006	00o m		0711	Ch Sign Xi = 0
0601	-		0407	Search
0713	square		1411	1411
0606	exch. x&y		0415	Recall Y
0603	divide		0004	004 Ln (q)
0605	↓		0602	multiply
0607	x		0605	↓
0604	↑		0400	+ direct
0414	store Y		0011	011
0001	001 k*		0408	MARK
0405	recall dir		1415	1415
0006	006 m		0415	recall y
0606	exch. x&y		0001	001 k*
0600	+		0405	recall dir
0606	exch. x&y		0012	012 Xi
0603	divide		0600	+
0605	↓		0701	1
0611	Ln x		0601	-
0404	store dir		0605	↓
0003	003 Ln (p)		0611	Ln x
0701	1		0400	+ direct
0606	exch. x&y		0011	011
0601	-		0405	recall dir
0605	↓		0012	012 Xi
0611	Ln x		0611	Ln x
0404	store dir		0401	- direct
0004	004 Ln (q)		0011	011
0408	MARK		0701	1
1412	1412		0401	- direct
0405	recall dir		0012	012 decr. Xi
0009	009 Xi		0415	recall y
0404	store dir		0012	012 Xi
0012	012		0701	1

Wang Calculator Program - continued.

0508	Skip if y < x	0405	rec direct
0407	Search	0011	011
1415	1415	0614	e ^x
0405	rec direct	0411	Write
0011	011	0105	(1.5) p(m,x,k)
0614	ex	0604	↓
0400	+ direct	0405	rec direct
0008	008	0002	002 N
0415	rec Y	0602	multiply
0008	008	0606	exch x&y
0405	rec direct	0411	Write
0009	009	0403	(4.3) Neg. Binomial Frequency
0004	SR(store x&y) 0004	0405	rec direct
0415	rec Y	0008	008
0302	032	0411	Write
0702	2	0105	(1.5) Cumulative p
0508	Skip if Y < X	0602	multiply
0100	Execute SR0100(calc.plot)	0605	↓
0114	Execute SR0114(execute plot)	0411	Write
0415	rec Y	0403	(4.3) Cumulative Frequency
0302	032	0408	Mark
0702	2	1514	1514
0508	Skip if Y < X	0701	1
0407	Search (Jump if flag < 2)	0400	+ direct
1514	1514	0009	009 incr. x
0015	Execute SR0015 (CR/LF)	0415	rec Y
0005	Execute SR0005(recall x&y)	0203	023 Xmax
0604	↑	0600	+
0405	rec direct	0600	+
0000	000 (score incr.)	0600	+
0602	multiply	0600	+ (Xmax + 4)
0701	1	0405	rec direct
0700	0	0009	009 x _i
0700	0	0508	Skip if Y < X
0606	exch x&y	0407	Search (loop for
0601	subtract	1412	1412 next x _i)
0605	↓	0515	STOP
0411	Write		
0302	(3.2) (Equivalent DRT Score)		
0005	Execute SR0005(recall x&y)		
0411	Write		
0200	(2.0) (Nr of listener errors)		

Appendix C

The Intelligibility Threshold Level (ITL):
A new Approach for Evaluating Performance of
Digital Speech Communications Processors

Caldwell P. Smith

Reprinted from ASA*50 Speech Communication Preprint Experiment,
Acoustical Society of America, June 1979

Intelligibility performance of voice processors has been typically specified in average intelligibility scores: values presumably equaled or exceeded by half the underlying populations of scores, assuming a normal distribution. However, extensive multi-speaker testing of a wide variety of processors over the past decade has shown conclusively that (1) populations of scores for processors typically deviate significantly from normal; (2) mean scores of individual talkers in multi-speaker tests typically show highly significant differences ($\alpha = .001$), and (3) significant differences among the mean scores for phonetic features are also typical. To further an implied objective of intelligibility testing: estimation of a level equaled or exceeded by the majority of scores, for example, 80% of a population of scores for talkers and phonetic features, a new approach has been established for evaluation, in which intelligibility data is analyzed to estimate intelligibility threshold levels (ITL's): levels equaled or exceeded by specified fractions of populations of scores, at a specified confidence level. The method, based on non-parametric statistics of the Kolmogorov-Smirnov type, involves rank-ordering a population of scores and constructing a cumulative distribution and its confidence band, from which ITL's can be readily assessed. Intelligibility data for various processors has typically shown larger differences in ITL's than occur with mean intelligibility scores.

INTRODUCTION.

Diagnostic intelligibility testing (Voiers, 1973; 1977) has been applied extensively to test and evaluation of a variety of speech communications processors and systems over the past decade; numerous test results have been published in the literature (for example, Voiers and Smith, 1972; Smith, 1977; 1979). Testing has usually served multiple objectives of providing a basis for comparing different speech processor algorithms or hardware, and guiding research to "fine tune" algorithms to obtain superior intelligibility or correct deficiencies, but also for estimating intelligibility predicted for the processor when used in a "real world" environment for support of voice communications for some population of talkers and listeners, presumably not too different from those used in conducting the tests. The average intelligibility scores customarily cited for voice systems carry the implication of representing values that would be equaled or exceeded by 50% of an underlying aggregate of scores for individual talkers, listeners, and phonetic features, a population sampled in the process of intelligibility testing, presumably normally distributed and representative of a "real world" communications environment.

RATIONALE FOR THE INTELLIGIBILITY THRESHOLD LEVEL (ITL) PERFORMANCE RATING

Even if populations of intelligibility scores obtained in multi-speaker tests were normally distributed - and there is considerable evidence that this is customarily not the case (Smith, 1979) - it would seem appropriate to reassess the practice of specifying performance in terms of average intelligibility scores. Instead, intelligibility levels estimating the values attained or exceeded by a majority in the populations of scores, for example 80% of the scores, at a specified confidence level, would seem to be more meaningful and relevant performance ratings, especially so for assessing voice systems required to support critical communications involving brief, terse messages and where misunderstandings, or time lost in requiring messages to be repeated, could result in severe cost penalties. From this perspective, a performance rating in the form of an intelligibility threshold level (ITL) is proposed: an experimentally determined intelligibility level (based on testing with appropriate talkers, listeners, and test items, such as current multi-speaker versions of the Diagnostic Rhyme Test) specifying a forecast of the intelligibility level that will be equaled or exceeded by a specified percentage of a population of intelligibility scores, at a stated confidence level.

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EXAMPLES OF INTELLIGIBILITY THRESHOLD LEVELS (ITL's)

Some examples of ITL's determined from distributions of diagnostic intelligibility scores of some well-known digital speech processors follow. Each was determined by utilizing the 24 basic diagnostic scores, i.e. the four scores ascertained for each of the six primary consonantal features tested with the Diagnostic Rhyme Test, forming a composite data table composed of feature scores of all speakers in the test. The composite table was then rank-ordered and used to construct a cumulative distribution. Except for the fact that each datum (score) represented an average of the responses of eight listeners, there was no averaging; for example, separate scores were included for voicing present (frictional), voicing present (non-frictional), voicing absent (frictional) and voicing absent (non-frictional) for each speaker, etc. The details of phonetic feature scores that typically reveal idiosyncrasies and deficiencies peculiar to a voice processor or algorithm are retained in the cumulative plots of scores. While the distributions do not reveal specific identities of features and speakers involved in particular "bad" scores, that information is readily available from the conventional listing of diagnostic scores when needed

for the purpose of diagnosing specific deficiencies.

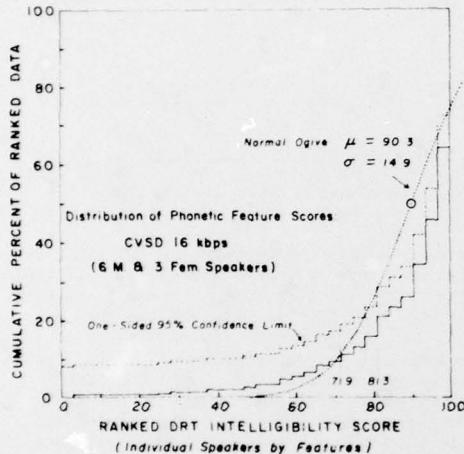


Fig. 1. Determination of ITL for 16 kbps CVSD.

Fig. 1 presents the distribution of scores from evaluation of continuous variable-slope delta modulation (CVSD) operating at 16 kilobits per second. A one-sided 95% confidence band, and the normal ogive for the mean and variance found in this data set from tests with nine talkers (6 male and 3 female) are shown. The ITL estimate from this data suggests that, at the 95% confidence level, 80% of the scores in populations for which the data is a random sample will equal or exceed 71.9. The 80% value in the actual data distribution was 81.3.

ALTERNATIVE DATA BASES FOR ITL's

Assuming that multi-speaker diagnostic intelligibility data has been established by formal intelligibility testing, several alternative methods can be considered for selecting the data base used in determining ITL's, differing in the basis of selecting an aggregate of scores for the assessment. One procedure has already been described above. Some other possibilities are (2) separating the population of scores previously described into sub-groups consisting of voiced and unvoiced scores respectively, and determining ITL's separately for the two categories; (3) averaging across phonetic feature scores obtained with each listener, thus creating a population of total intelligibility scores, one for each speaker/listener combination, and (4) utilizing the separate scores obtained for every speaker/feature/listener combination.

Application of method (2) is illustrated in Fig. 2. The diagnostic scores for 16 kbps CVSD of Fig. 1 were separated into groups representing voiced and unvoiced features; separate rankings and ITL's were established for the two groups. The data represent a trend found in scores for voice processors, in which values of ITL's for voiced features are higher, and unvoiced features lower, than the ITL values for the total population of scores. Further comparisons are shown in

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Table I, which presents ITL ratings from total aggregates of scores (as described in the first method) and separate ITL's for the data separated into populations of voiced and unvoiced feature scores. The comparisons suggest that the greatest potential for improving intelligibility will lie in improving the modeling of unvoiced speech events.

Method (3), using distributions of total intelligibility scores (for individual listeners and speakers) was found to result in distributions approximately normal with a single speaker, but deviating significantly with multiple speakers (on a basis of Lilliefors test results). However, in all cases these distributions were much less skewed than distributions of diagnostic scores for phonetic features. Method (3) reveals variations in listener performance not revealed by the first method described; however, listener variations have been found to be much smaller than variations due to phonetic features or due to speakers. A major limitation of method (3) is the failure to reveal significant deficiencies among the feature scores. For this reason, evaluation by this grouping of data is considered to have limited value.

Method (4) would offer composite information about talkers, phonetic features, and listeners. However, it poses a major shortcoming: the 192-word Diagnostic Rhyme Test includes only eight tokens for each of the 24 feature states. Consequently method (4) would result in distributions with extremely gross quantization of the scale (nine possible values for the scores) resulting in inadequate resolution.

Steps in determining ITL's (using the first method described) are as follows:

1. Rank-order the population of intelligibility scores comprised of the 24 feature-state (or "sub-feature") scores of each talker, combined into an aggregate data population.
2. Using the ranked table, construct the cumulative distribution of scores. For this purpose, each datum is interpreted as a segment of $(1/n \times 100)\%$.
3. Construct a confidence band, using an appropriate quantile from a table of values of the Kolmogorov test statistic (Conover, 1971) or the value $Q = 1.22/\sqrt{n}$ (for a one-sided band at $p = .95$, and $n > 40$). (Note that with 24 feature scores for each of six speakers, $Q = .0983$, or 9.83%). In reference to the figures, the value of Q designates an amount of vertical displacement of the data distribution required to define the specified confidence band.
4. To obtain desired ITL's, read from the confidence band profile the corresponding intelligibility level. This can be done graphically, or for greater accuracy, from the listing of ranked scores and associated cumulative percentages (as done with the examples of ITL's presented here).

PROPOSED ADVANTAGES OF THE INTELLIGIBILITY THRESHOLD LEVEL (ITL) RATING.

It is proposed that ITL ratings have several advantages over average intelligibility scores for rating intelligibility performance of voice communications processors:

1. An ITL rating assesses intelligibility performance attained for the majority of scores rather than the average score. The rating provides information as to whether a voice processor caused a significant proportion of "bad" scores for any combinations of speaker and phonetic features.
2. A confidence level is defined for the ITL rating.
3. The ITL rating, based on non-parametric properties of the distribution of scores, is valid without regard to the form of the distribution of scores, and is not affected by departure from normality.
4. The rating is inherently compensated for the number of speakers and/or the number of replications of a test.
5. ITL ratings for various processors have been found to show greater differences among processors than revealed by average scores.
6. The ITL does not require any new testing method; given detailed data, it is applicable for evaluating intelligibility data not only for the Diagnostic Rhyme Test or DRT, but also for the Modified Rhyme Test or MRT (House et al., 1955) or the Consonant Recognition Test or CRT (Preusse, 1959). However, details of diagnostic scores by speakers and features are known only for the Diagnostic Rhyme Test.

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TABLE I COMPARISONS OF INTELLIGIBILITY THRESHOLD LEVELS (ITL's)
from Diagnostic Rhyme Test Scores, 6 Male & 3 Female Speakers

and 8 Listeners

PROCESSOR	Mean Score	80% Intelligibility Threshold Level (95% Confidence)*		
		Voiced	Unvoiced	Total
CVSD 9.6 kbps	80.1	62.5	25.0	53.1
CVSD 16 kbps	90.3	81.3	56.3	71.9
CVSD 32 kbps	95.0	90.6	71.9	87.5
Ch Vocoder 2400	83.0	62.5	37.5	59.4

* There is 95% confidence that 80% of the population of diagnostic intelligibility scores (feature scores, by Speakers) will equal or exceed the stated value.

It is hypothesized that ITL ratings may be more closely correlated with user acceptance of digital speech processors than are average intelligibility scores; however, no data has been available to permit a test of this hypothesis.

CONCLUSIONS.

The relatively new techniques of multi-speaker diagnostic intelligibility testing have tended to overwhelm the evaluator with the mass of information contained in typical intelligibility test results. Perhaps because of the difficulties of evaluating and interpreting fine details of performance, there has been a tendency to reduce results to single numbers: the average intelligibility scores, values that provide no information as to variations among individual speakers and among scores for phonetic features, even though the salient differences in various speech processor algorithms are usually revealed in these details. Preparation of cumulative distributions of scores can provide a means for summarizing entire populations of scores in meaningful but compact form that contains the significant variations and highlights deficiencies. Preparation of confidence bands for distributions can permit forecasts of intelligibility threshold levels (ITL's) for selected proportions of scores at specified confidence levels. Studies of ITL ratings of intelligibility performance obtained with various speech processors operating under a variety of conditions should provide guidance for determining minimum ITL standards that would be appropriate performance criteria for various applications in communication.

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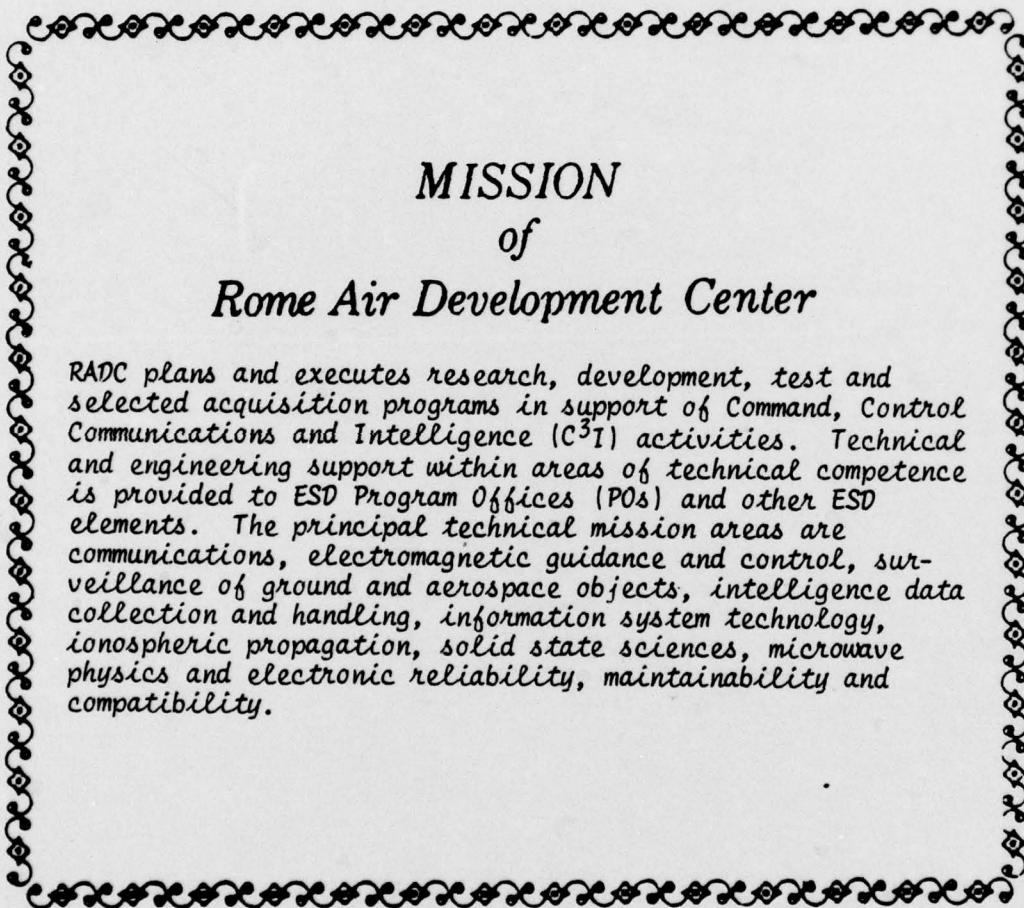
Appendix D

Table of the Kolmogorov Test Statistic

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Table D1. Quantiles of the Kolmogorov Test Statistics

One-Sided Test							p=.90							p=.95							p=.99						
	p=.90	.95	.975	.99	.995			p=.90	.95	.975	.99	.995			p=.90	.95	.975	.99	.995			p=.90	.95	.975	.99	.995	
n=1	.900	.950	.975	.990	.995		n=21	.226	.259	.287	.321	.344			.221	.253	.281	.314	.337			.216	.247	.275	.307	.330	
2	.684	.776	.842	.900	.929		22								.23	.216	.247	.275	.307			.216					
3	.565	.636	.708	.785	.829		23								.24	.212	.242	.269	.301			.212					
4	.493	.565	.624	.689	.734		24								.25	.208	.238	.264	.295			.208					
5	.447	.509	.563	.627	.669		25																				
6	.410	.468	.519	.577	.617		26																				
7	.381	.436	.483	.538	.576		27																				
8	.358	.410	.454	.507	.542		28																				
9	.339	.387	.430	.480	.513		29																				
10	.323	.369	.409	.457	.489		30																				
11	.308	.352	.391	.437	.468		31																				
12	.296	.338	.375	.419	.449		32																				
13	.285	.325	.361	.404	.432		33																				
14	.275	.314	.349	.390	.418		34																				
15	.266	.304	.338	.377	.404		35																				
16	.258	.295	.327	.366	.392		36																				
17	.250	.286	.318	.355	.381		37																				
18	.244	.279	.309	.346	.371		38																				
19	.237	.271	.301	.337	.361		39																				
20	.232	.265	.294	.329	.352		40																				
Approximation for n > 40:														<u>1.07</u>	<u>1.22</u>	<u>1.36</u>	<u>1.52</u>	<u>1.63</u>									
														<u>\sqrt{n}</u>	<u>\sqrt{n}</u>	<u>\sqrt{n}</u>	<u>\sqrt{n}</u>	<u>\sqrt{n}</u>									



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